Location and Size of Distributed Generation Using a Modified Water Cycle Algorithm

John Edwin Candelo Becerra [#1], Helman Enrique Hernández Riaño [*2], Rodrigo Ramirez Pisco [**3]

[#] Department of Electrical Energy and Automation, Universidad de Nacional de Colombia,
Carrera 80 No. 65–223, Núcleo Robledo, Medellin - Colombia
[1] jecandelob@unal.edu.co
[*] Department of Industrial Engineering, Universidad de Córdoba, Carrera 6 No. 76-103 Montería – Colombia
[*] Department of Industrial Engineering, Universidad del Norte, Km. 5 Vía Puerto Colombia Barranquilla - Colombia
[2] hhernandez@correo.unicordoba.edu.co
[**] Department of Electrical Engineering, Universidad Politécnica de Cataluña, Avda. Diagonal 647, 08028 Barcelona – España
[**] Fundación para la Sostenibilidad Energética y Ambiental FUNSEAM, c/Baldiri Reixac 4 Torre I, Piso 7 | 08028 Barcelona - España
[3] director@funseam.com

Abstract—This paper presents a modified water cycle algorithm (WCA) adapted to the problem of finding the location and size of distributed generation (DG). Power losses minimization was used as an objective function to compare the proposed algorithm with particle swarm optimization (PSO), the bat-inspired Algorithm (BA), and harmony search (HS). The test scenarios consisted of locating five to seven generators with a maximum real and reactive power in the 33-node and 69-node radial distribution networks. The experiment was designed to start iterations from the same initial population to identify the algorithms' performance when searching for the best solutions. The results demonstrate that the modified WCA found the minimum power losses after locating and sizing distributed generators for most of the test scenarios. The algorithm converged quickly to the best solution and the solutions for all repetitions tested were close to the best for each case simulated.

Keywords: bat-inspired algorithm, harmony search, particle swarm optimization, water cycle algorithm, power losses, distributed generation, distribution network

I. INTRODUCTION

Power losses are a concern for electricity companies, especially when they represent high percentages of the total power transfer during the operation of power networks. There are many ways to mitigate power losses, such as feeder restructuring [1], distributed generation (DG) placement [2]–[8], capacitor placement [1], [8], and network reconfiguration [9], [10].

DG is one of the most appropriate methods to minimize power losses due to the installation of generators close to the loads. Several techniques have been tested to locate and size DG, but metaheuristics are preferred for problems with large numbers of combinations, although the problem of finding a global optimum is sometimes an issue.

Some of the algorithms used to solve this problem are particle swarm optimization (PSO) [11]–[14], the ant colony (AC) [15], [16], the evolutionary algorithm (EA) [17]–[19], simulated annealing (SA) [20]–[22], the bat-inspired algorithm (BA) [23], [24], harmony search (HS) [25], [26].

Some convergence problems have been detected when testing difficult DG placement and sizing problems [24], [27] because of the distribution network selected, the number of possible nodes, the number of generators to locate, and the size of the generators. The number of combinations to solve this problem is high and not easy for some algorithms to compute.

Other concerns are adopting good solutions with the algorithms within the time needed, avoiding local solutions in the security of convergence to the global optimum, and finding the best solutions with minimum repetitions of the simulations. Improvement of these features could reduce the evaluation time for more difficult problems, considering the large number of power flows evaluated to meet all the constraints.

The water cycle algorithm (WCA) has been proposed to solve several functions [28] and to find better solutions converging to the optimum. In this paper, the WCA was modified and adjusted to solve the problem of location and size of DG with the objective function of minimizing power losses. The aim of this work is to find an improved algorithm that will solve a combinatorial problem with the possibility to place and size DG with consistent results through all iterations and repetitions.

PROBLEM FORMULATION

The total real power losses of a distribution network can be represented using (1) [29].

$$P_{Loss}=\sum_{i=1}^{n}\sum_{j=1}^{n}A_{ij}(P_iP_j+Q_iQ_j)+B_{ij}(Q_iP_j+P_iQ_j) \quad (1)$$

Where P_i is the real power injected to the node i, Q_i is the reactive power injected to the node i, P_j is the real power injected to the node j, and Q_j is the reactive power injected to the node j. The parameters A_{ij} and B_{ij} are defined in (2) and (3), respectively.

$$A_{ij}=\frac{R_{ij}\cos(\delta_i-\delta_j)}{V_iV_j} \quad (2)$$

$$B_{ij}=\frac{R_{ij}\sin(\delta_i-\delta_j)}{V_iV_j} \quad (3)$$

Where R_{ij} is the resistance between the nodes i and j, V_i is the voltage magnitude of the node i, δ_i is the voltage angle of the node i, V_j is the voltage magnitude of the node j, and δ_j is the voltage angle of the node j.

The best fitness is defined as the minimum power losses of all possible solutions found with the algorithms, as expressed in (4).

$$F_{best}=\underset{i=1..n}{Min}(P_{Lossi}) \quad (4)$$

Where F_{best} is the best fitness calculated as the minimum power losses obtained when evaluating all solutions proposed by the algorithms *(i=1…n)*, P_{Lossi} is a vector containing all the solutions of power losses found with the power flow, and n represents the maximum number of evaluations contained in the vector. As the vector P_{Lossi} is updated with new evaluations, F_{best} is recalculated.

This objective function is subject to the real and reactive power balance of the distribution network, as expressed in (5) and (6).

$$P_{Slack}+\sum_{i=1}^{n}P_{DGi}=\sum_{i=1}^{n}P_{Di}+P_{Loss} \quad (5)$$

$$Q_{Slack}+\sum_{i=1}^{n}Q_{DGi}=\sum_{i=1}^{n}Q_{Di}+Q_{Loss} \quad (6)$$

Where P_{Slack} is the real power supplied from the main source, P_{DGi} is the real power supplied from the DG located at node i, P_{Di} is the real power consumed by the load at node i, and P_{Loss} is the total real power of the distribution network. Q_{Slack} is the reactive power supplied by the main source, Q_{DGi} is the reactive power supplied by the DG located at node i, Q_{Di} is the reactive power consumed by the load at node i, and Q_{Loss} is the total reactive power of the distribution network.

Voltage magnitudes of each node i, $|V_i|$, must comply with the minimum voltage magnitude, $|V_i|^{\min}$, and the maximum voltage magnitude, $|V_i|^{\max}$, as expressed in (7).

$$|V_i|^{\min}\le|V_i|\le|V_i|^{\max} \quad (7)$$

The real and reactive power supplied by the DG is limited to the minimum and maximum values, as defined in (8) and (9).

$$P_{DGi}^{min}\le P_{DGi}\le P_{DGi}^{max} \quad (8)$$

$$Q_{DGi}^{min}\le Q_{DGi}\le Q_{DGi}^{max} \quad (9)$$

Where, P_{DGi} is the real power of generators located at node i, $P_{\mathrm{DGi}}^{\min}$ is the minimum real power of generators located at node i, and $P_{\mathrm{DGi}}^{\max}$ is the maximum real power of generators located at node i. Q_{DGi} is the reactive power of generators located at node *i*, $Q_{\mathrm{DGi}}^{\min}$ is the minimum reactive power of generators located at node *i*, and $Q_{\mathrm{DGi}}^{\max}$ is the maximum reactive power of generators located at node *i*.

Finally, the current circulating through the branches of the distribution network must be limited to the maximum current accepted, as shown in (10) and (11).

$$i_{ij} \le i_{ij}^{max} \tag{10}$$

$$i_{ji} \le i_{ji}^{max} \tag{11}$$

Where i_{ij} is the current of the branch circulating from node *i* to node *j*, and i_{ji} is the current of the branch circulating from node *j* to node *i*. $i_{ij}^{\max}$ is the maximum current of the branch circulating from node *i* to node *j*, and $i_{ji}^{\max}$ is the maximum current of the branch circulating from node *j* to node *i*.

ALGORITHMS

A. Codification for the search

Figure 1 shows the codification of the problem for locating and sizing DG. The vector is formed by the elements that represent the DG's real power, reactive power, and position.

x_1	y_1	z_1	x_2	y_2	z_2	…	x_d	y_d	z_d	…	x_{nd}	y_{nd}	z_{nd}

Fig. 1. Problem codification for location and size of distributed generators

Where *x*, *y*, and *z* represent the real power supplied, the reactive power supplied, and the number of the node where the generator is located, respectively. The number of generators is represented by *nd*.

B. Bat-inspired Algorithm

This algorithm is based on the echolocation of bats during the search for a prey [30]. An initial population is defined, and the frequency and velocity is used to move all bats. Random flies help to find new solutions in the searching region.

The steps of this algorithm are as follows:

(1) Define the frequency f_i using (12), the pulse rate r_i, and the loudness A_i.

(2) Initialize the population and the velocities of the bats.

(3) Evaluate the fitness and select the best.

(4) Use the fitness vector to rank the solutions as F_{best}.

(5) While $iter < iter^{max}$:

- (a) With the frequency defined in (12) and the velocities defined in (13), find the new solutions of x_{new} using (14)
- (b) If $rand > ri$
  - • Create a new solution close to the best
- (c) End if
- (d) Use random flies of bats to create new solutions
- (e) Find the new fitness $F_{new}(x_{new})$
- (f) if ($F_{new} < F_{best}$ and $rand < Ai$)
  - • Update the solution
- (g) End if
- (h) Increase r_i and reduce A_i
- (i) Rank the solutions and update the best fitness F_{best}

(6) End while

The frequency f_i can be calculated using (12), and the velocity is defined using (13) [31].

$$f_i = f_{\min} + \left(f_{\max} - f_{\min}\right) * \beta \tag{12}$$

$$v_i^k = v_i^{k-1} + (x_i^k - x_{best})\, f_i \tag{13}$$

Where f_{max} is the maximum frequency, f_{min} is the minimum frequency, and β is a random number to generate different frequencies. v_i^k is the velocity of the bat i at the iteration k, v_i^{k-1} is the velocity of the bat i at the iteration k-1, x_i^k is the position of the bat i at the iteration k, and x_{best} is the best position of the bats.

The new position of the particle, x_i^k, is updated after adding the new velocity, v_i^k, to the previous position x_i^{k-1}, as shown in (14).

$$x_i^k = x_i^{k-1} + v_i^k \tag{14}$$

This algorithm converges to the solutions found quickly and obtains good results in a few iterations [23], [24].

C. Particle Swarm Optimization

This metaheuristic is based on the social behavior of birds during flight [32]. The algorithm generates an initial population, and with an iterative and stochastic method, the search for the best positioned is performed.

The algorithm implemented in this work is based on [22]:

(1) Define the parameters of the algorithm.

(2) Initialize the population and the velocities of particles.

(3) Evaluate the fitness and select the best particles.

(4) While the number of generations is lower than the limit *nr*, do:

- (a) Update the velocity of all particles using (15)
- (b) Update the new position of particles using (16)
- (c) Find new best solutions

(5) End while.

The velocity of particles is found using (15).

$$v_i^{k+1} = w * v_i^k + \varphi_1 * rand_1 * (pbest_i - x_i^k) + \varphi_2 * rand_2 * (g_i - x_i^k) \tag{15}$$

Where v_i^{k+1} is the new velocity of the particle i, w is the factor of inertia of the particle i, φ_1 and φ_2 are weights to control the cognitive and social components, and $rand_1$ and $rand_2$ are uniformly distributed random numbers between zero and one.

Each particle's new position is calculated using the current position and the new velocity, as shown in (16).

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{16}$$

Where x_i^{k+1} is the new position of the particle i, x_i^k is the previous position of the particle i, and v_i^{k+1} is the new velocity calculated with (15).

Several applications for the planning of DG systems have been presented using this algorithm [33-37].

D. Harmony Search

This metaheuristic algorithm is based on a population that mimics the natural behavior of musicians playing instruments together to achieve a fantastic aesthetic harmony [32]. This algorithm can explore the search space of a set of data contained in the parallel optimization environment, where every solution (harmony) vector is generated intelligently by the exploration and exploitation of a search space. Its many features make it a preferable technique not only as an independent algorithm, but also when combined with other metaheuristic algorithms.

The steps of the algorithm are defined as follows:

(1) Define the initial parameters.

(2) Initialize the population in the vector *HM*.

(3) Rank the solutions and select the best positioned with their fitness F_{best}.

(4) While $iter < iter^{max}$:

- (a) Generate new solution x_{new}
- (b) Calculate the fitness for the new solution
- (c) Update the vector *HM*
- (d) Update the best harmony vector
- (e) Rank the solutions and select the best positioned with their fitness F_{best}

(5) End while.

The algorithm is based on the generation of a vector's initial population, which is used later to combine solutions with the current values obtained from simulations. This is advantageous, for it allows the generation of new solutions with the best positioned solutions inside the vector.

E. Water Cycle Algorithm

Similar to other metaheuristic techniques, this algorithm is based on an initial population set. After the initial evaluation of the population, the best positioned is selected as the sea. Others solutions are ranked as rivers and streams, continuing with the search by using the direction of the streams following the rivers, and the rivers following the sea [28].

The steps of the algorithm are presented as follows [28]:

(1) Choose the initial parameters *Nsr*, *dmax*, *Npop*, and *Max_iter*.

(2) Generate a random initial population.

(3) Form the initial raindrops, rivers, and sea [28].

(4) Evaluate the cost of raindrops and the intensity of flows for the rivers and the sea [28].

(5) While *iter* < *itermax*:

- (a) Each stream flows to the rivers using (17), and each river flows to the sea using (18)
- (b) Change position if the stream has a better position than the river
- (c) Change position if the river has a better position than the sea
- (d) If the evaporation condition is satisfied
  - Start the raining process with (20) and (21)
- (e) End if
- (f) Update the value of *dmax* with (19)

(6) End while.

The new positions of streams are calculated using (17), and the position of rivers is updated using (18).

$$x_{Stream}^{k+1} = x_{Stream}^{k} + rand * C * (x_{River}^{k} - x_{Stream}^{k}) \tag{17}$$

$$x_{River}^{k+1} = x_{River}^{k} + rand * C * (x_{Sea}^{k} - x_{River}^{k}) \tag{18}$$

Where x_{Stream}^{k+1} is the new position of the stream, x_{Stream}^{k} is the current position of the stream, x_{River}^{k+1} is the new position of the river, x_{River}^{k} is the current position of the river, x_{Sea}^{k} is the current position of the sea, *rand* is a uniformly distributed random number and *C* is a number between 1 and 2.

The distance between the river and the sea, d_{max}, is updated after each iteration, as expressed in (19) [28].

$$d_{\max}^{k+1} = d_{\max}^{k} + \frac{d_{\max}^{k}}{\max \quad iteration} \tag{19}$$

The raining process for the streams is conducted randomly using (20) and (21) [28].

$$x_{Stream}^{new} = LB + rand * (UB - LB) \tag{20}$$

$$x_{Stream}^{new} = x_{Sea} + \sqrt{\mu} * randn(1, N_{Var}) \tag{21}$$

Where x_{Stream}^{new} is the new position of the stream generated randomly, x_{Sea} is the current position of the sea, *LB* is the minimum value of the position, *UB* is the maximum value of the position, μ is a coefficient which shows the range of searching region near the sea, and *randn* is a normally distributed random number.

This algorithm is adapted to the problem of location and size of DG in radial distribution systems. The algorithm is modified to achieve similar conditions for comparison with other algorithms and to accelerate the search for the best solutions. Changes to the algorithm are proposed to create a similar number of simulations to compare all algorithms; the condensation process was relocated to evaluate the process for the rivers and streams continuously. The steps implemented in this paper are presented as follows:

(1) Choose the initial parameters *Nsr*, *dmax*, *Npop*, and *Max_iter*.

(2) Generate a random initial population.

(3) Form the initial raindrops, rivers, and sea [28].

(4) While *iter* < $iter^{max}$:

(a) For i=1:n

If i is a river

- If evaporation of the river is satisfied
  a. Start the raining process with (22) and (23)
- Else
  b. Each river flows to the sea using (18)
  c. Change position if the river has a better position than the sea
- End if

End if

If i is a stream

- If evaporation of the stream is satisfied
  d. Start the raining process with (20) and (21)
- Else
  e. Each stream flows to a river selected randomly using (17)
  f. Change position if the stream has a better position than the river
- End if

End if

(b) End for

(c) Reduce the value of *dmax* with (19)

(d) Rank the solutions and select the best positioned with their fitness F_{best}

(5) End while.

The raining process for the rivers is conducted randomly using (22) and (23) [28].

$$x_{River}^{new} = LB + rand * (UB - LB) \tag{22}$$

$$x_{River}^{new} = x_{sea} + \sqrt{\mu} * randn(1, N_{Var}) \tag{23}$$

Where x_{River}^{new} is the new position of the stream generated randomly, x_{Sea} is the current position of the sea, *LB* is the minimum value of the position, *UB* is the maximum value of the position, μ is a coefficient which shows the range of searching region near the sea, and *randn* is a normally distributed random number.

TEST SYSTEMS AND SIMULATIONS

The proposed method was tested using the 33-node and 69-node radial distribution networks with parameters found in [33]–[35]. General information of both distribution networks is presented in Table I.

TABLE I. Specification of the Distribution Networks [33]–[35].

Elements	33-node test feeder	69-node test feeder
Nodes	33	69
Lines	32	68
Slack	1	1
Transformers	0	0
Loads	32	49

Figure 2 shows the single-line diagram of the 33-node radial distribution network [33], [34]. This case had a total load of 3715 KW and 2300 kVAr and a total power supply of 3926 KW and 2443 kVAr. Voltage limits were defined as *Vmin* = 0.9 p.u. and *Vmax* = 1.1 p.u.

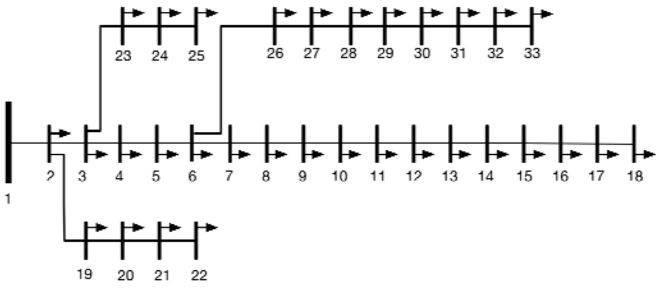


Fig. 2. Case 33-node radial distribution network [33]

Figure 3 shows the 69-node radial distribution network [33], [35]. This distribution network had a total load of 4014 KW and 2845 kVAr and a total generation of 4265 KW and 2957 kVAr. Voltage limits were defined as *Vmin* = 0.9 p.u. and *Vmax* = 1.1 p.u.

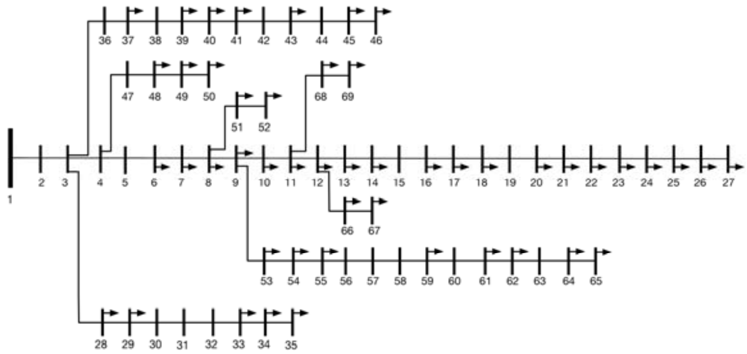


Fig. 3. Case 69–node radial distribution network [33]

These two radial distribution networks were used to test the BA, PSO, HS, and WCA when installing DG. Both distribution networks have a slack node that is not used to locate new generation; nevertheless, the rest of the nodes are possible candidates. The number of combinations increases with the number of nodes, so the case 69-node network is more difficult for finding good solutions.

A. Simulations

To test the algorithms, some case studies considered finding the location and size of five, six, and seven generators. The greater the number of generators to install, the more difficult it was to solve the problem for the two distribution networks. The algorithms were tested considering 200 individuals, 500 iterations, and ten repetitions. The same initial population was generated for all algorithms to evaluate performance starting from the same initial point.

RESULTS AND DISCUSSION

Table II shows the results obtained from the simulations performed with the PSO, BA, HS, and WCA. According to the experiment, similar reductions of power losses were found with all algorithms considering the number of individuals, iterations, and repetitions.

In this table, *Case* refers to the distribution networks, *Gen* is the number of generators, *Alg* is the type of algorithm used to find the solution, *Ptot* is the sum of the power installed in the power system, *Ploss* is the objective function of power losses, and *Pos* is the rank of the minimum solution found for each scenario.

TABLE III. Results of all algorithms for the 33-node and 69-node radial distribution networks. Source: The authors.

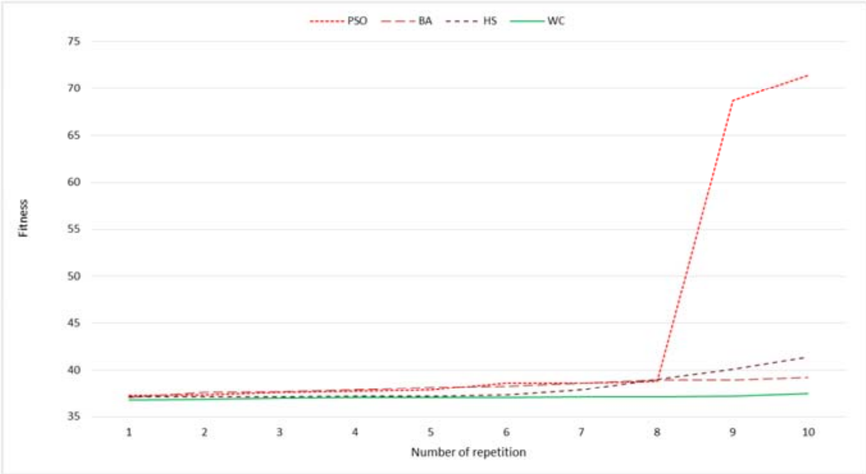
Case	Gen	Alg	Nodes	Ptot (kW)	Ploss (kW)	Pos
33-node	0	-	0	0	210.9	-
	5	PSO	14 30 32 24 7	3396.3	35.50	4
		BA	14 30 32 24 7	3442.3	35.46	2
		HS	6 31 15 24 10	3452.6	35.49	3
		WCA	32 30 24 14 7	3429.5	35.44	1
	6	PSO	6 9 30 32 15 24	3480.3	34.32	2
		BA	30 10 25 32 6 16	3468.9	34.40	3
		HS	32 25 30 12 14 7	3346.0	35.03	4
		WCA	7 30 24 16 11 32	3452.9	34.21	1
	7	PSO	7 10 15 21 24 30 32	3494.6	33.56	3
		BA	24 25 16 30 6 11 32	3488.4	33.06	2
		HS	7 25 29 14 9 24 32	3631.2	33.96	4
		WCA	10 32 16 24 21 6 30	3708.0	33.03	1
69-node	0	-	0	0.0	265.0	-
	5	PSO	50 12 61 69 23	3725.7	37.47	4
		BA	12 50 61 53 22	4111.9	37.38	3
		HS	8 12 61 49 23	3872.2	37.13	2
		WCA	61 11 49 25 18	4072.2	37.13	1
	6	PSO	23 67 11 50 65 61	3441.4	37.28	4
		BA	61 50 15 64 24 10	3674.5	37.04	2
		HS	44 12 8 50 23 61	3520.2	37.11	3
		WCA	50 25 9 61 17 12	3695.9	36.81	1
	7	PSO	2 27 38 50 22 11 61	3756.3	37.39	4
		BA	2 11 22 49 57 61 64	4797.8	36.96	2
		HS	64 68 11 6 50 61 23	4068.3	37.14	3
		WCA	64 17 61 11 8 25 50	4086.0	36.22	1

After running the ten repetitions, the modified WCA found the best solutions for the most cases compared with the other algorithms. For most of the cases, the BA solutions were good, confirming the results found in [24]. The HS algorithm found better results for the 69-node radial distribution network, confirming that this algorithm is good for a large number of combinations. The PSO had no good performance for the cases analyzed, but its solutions were close to the best solutions for all the scenarios with the number of repetitions performed in this study.

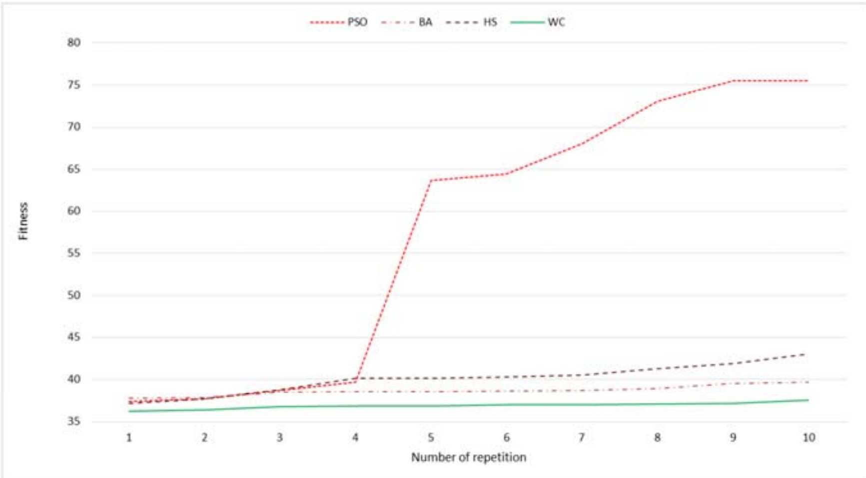
For the 33-node radial distribution network, the location of the five generators brought no complications for the algorithms, with findings of similar reductions in power losses. For six generators, the PSO, BA, and WCA obtained similar reductions in power losses. For seven generators, the WCA provided the best solutions, followed by the PSO, BA, and HS.

For the 69-node radial distribution network, the WCA found the best locations for all the cases studied, the HS and BA provided good solutions, and the PSO obtained the worst solutions. The location of the five generators brought no complications for the algorithms, with findings of similar reductions in power losses. For six generators, the WCA obtained the best results, followed by good results from the BA, HS, and PSO. For seven generators, the WCA provided the best solutions, followed by the BA, HS, and PSO.

Figures 4a and 4b show the solutions of the algorithms for the ten repetitions performed in the 33-node and 69-node radial distribution networks, respectively. In these figures, the *fitness* is used to compare the algorithms with the solutions found at each repetition. The solutions in these figures were organized from the minimum to the maximum value for each algorithm.



(a)



(b)

Fig. 4. Minimum solutions for all repetitions in (a) the 33-node radial distribution network, and (b) the 69-node radial distribution network. Source: The authors

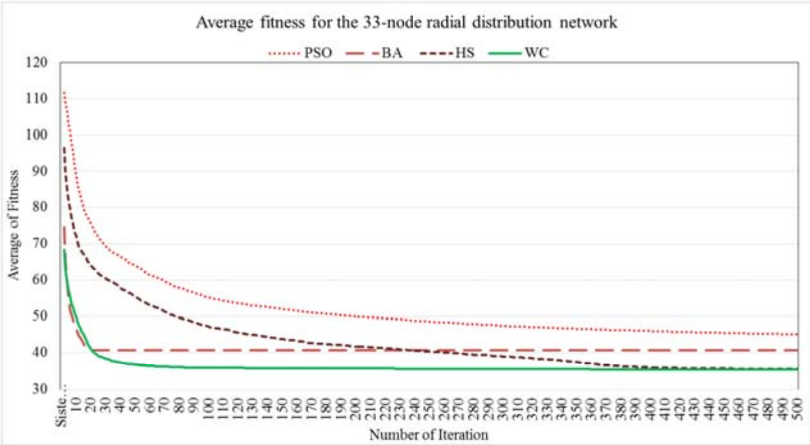
The PSO found better results for the 33-node network than for the 69-node network; some repetitions show that the solutions found were very high, which creates doubt for finding good solutions for the problem.

The HS found good solutions for a great number of the cases, but the solutions were not always good. The HS provided good solutions for the 33-node case, but its solutions for the 69-case were higher than the found with the other algorithms.

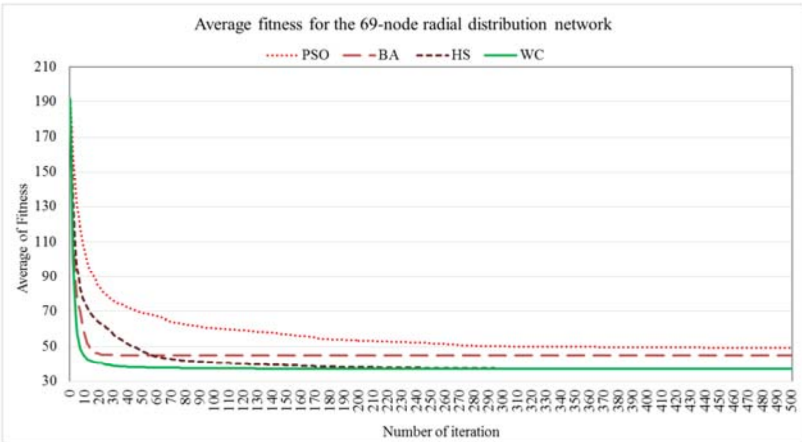
Although some of its solutions were higher than the best solutions found, the BA found good results for both power systems and for all repetitions, confirming it is a good method.

The WCA found the best solutions for the different repetitions in both distribution networks. The results demonstrate that the results obtained with the WCA were always the minimum values for all repetitions. This result provides reassurance that using the modified WCA can find a good solution regardless of the repetitions of simulations.

Figures 5a and 5b show the convergence of the algorithms for the 33-node and the 69-node radial distribution networks, respectively. The curves were computed using the mean of the solutions contained in the population after each iteration. This curve was plotted with the solutions evaluated from the 500 iterations tested in this work, representing how the population behaves.



(a)



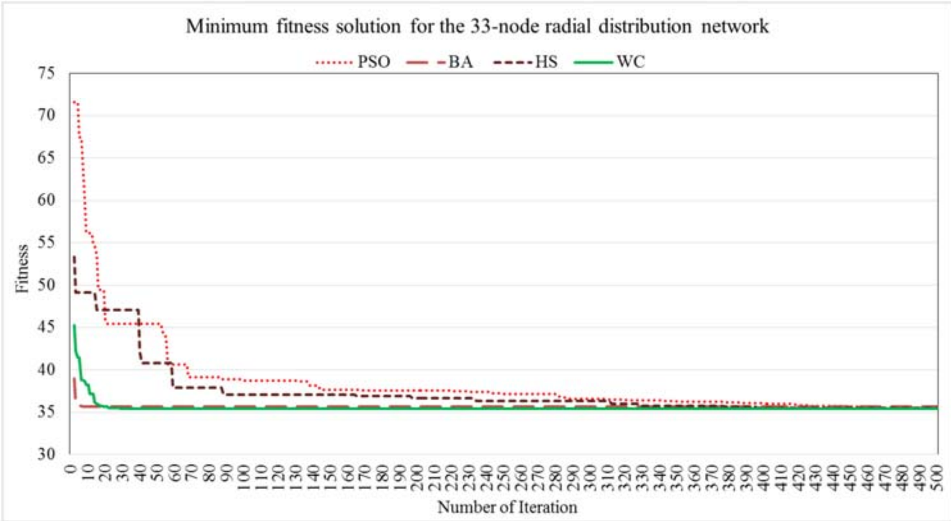
(b)

Fig. 5. Convergence of algorithms in (a) the 33-node radial distribution network, and (b) the 69-node radial distribution network. Source: The authors

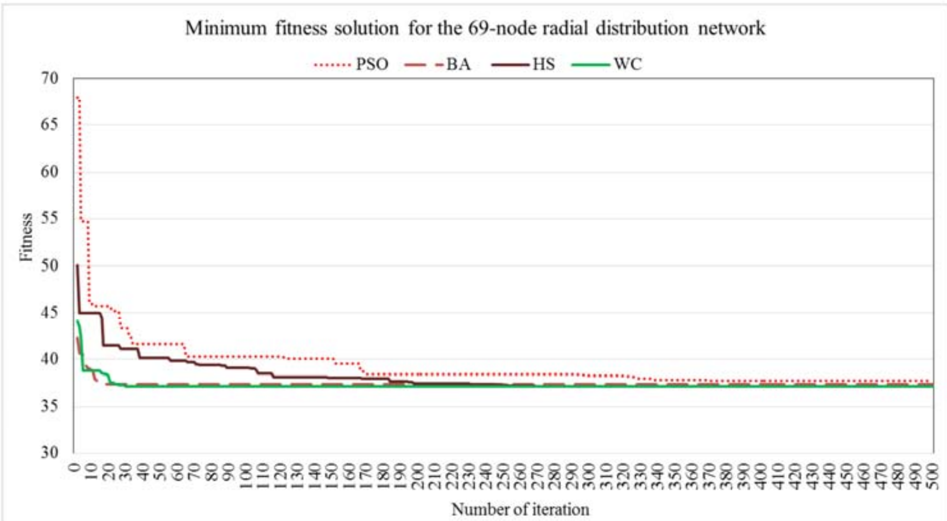
The PSO's average solutions were high throughout the iterations, as shown in previous research [24], [27]. The BA quickly reduced the fitness average, but the algorithm got trapped and remained this way for the rest of the iterations. The HS algorithm needed a large number of iterations to find good solutions, while the WCA quickly found the best solutions.

Comparing the behavior of these algorithms for the different distribution network cases, all showed similar results, but the WCA was the fastest algorithm in finding the minimum value. The HS was faster for the 69-node network compared to the solution found for the 33-node network, reducing the time to find good solutions and reaching the best solutions found with the WCA, although requiring a larger number of iterations.

Figures 6a and 6b show the minimum fitness solutions found after the ten repetitions tested in the 33-node and 69-node radial distribution networks, respectively. These figures show the minimum fitness and the evolution of the best points found throughout all the iterations of the algorithms, for the purpose of locating five generators in both distribution networks.



(a)

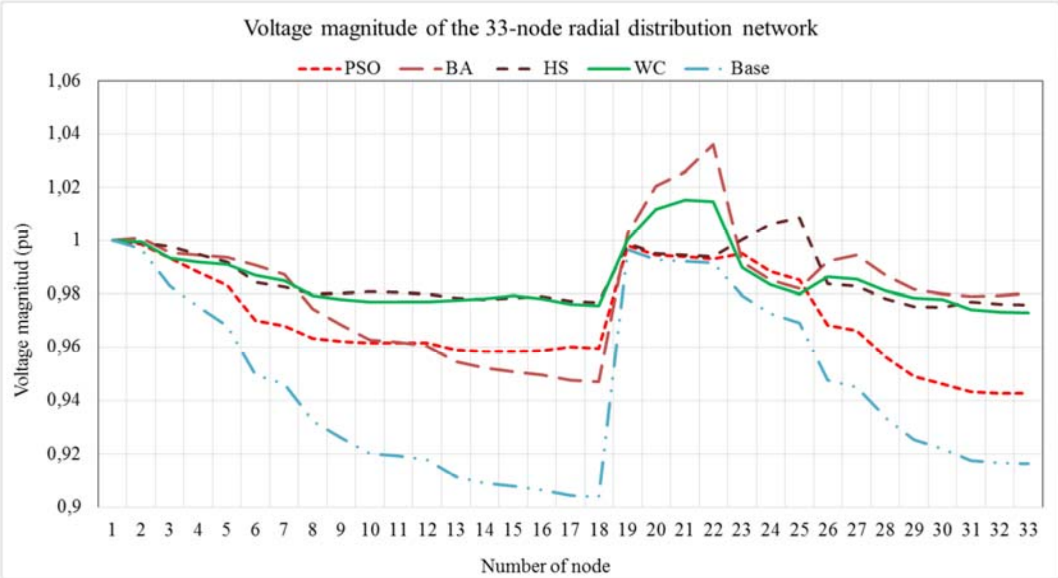


(b)

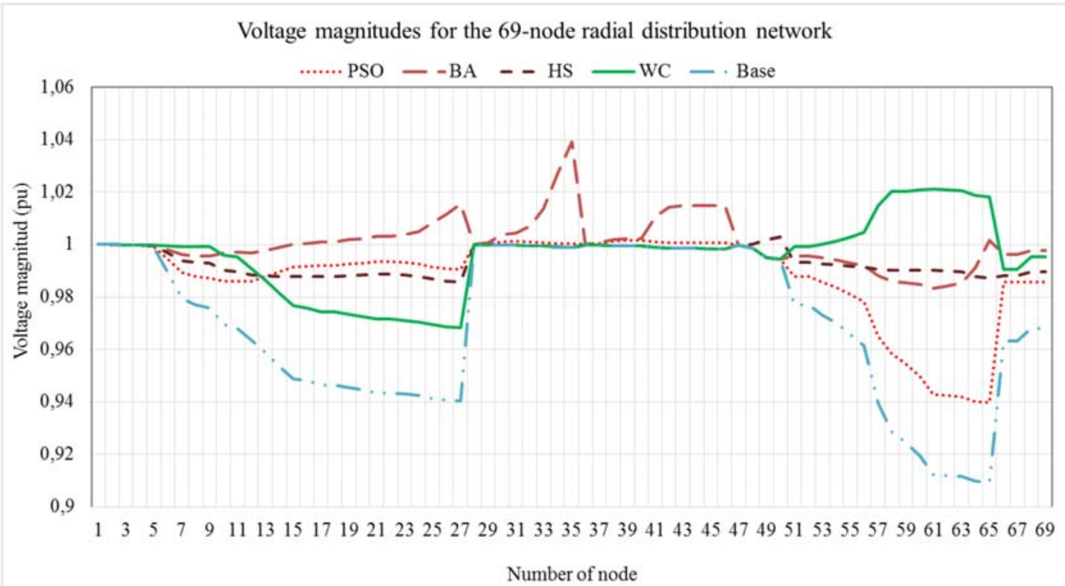
Fig. 6. Minimum solution found with the algorithms in (a) the 33-node radial distribution network, and (b) the 69-node radial distribution network. Source: The authors

For both radial distribution networks, the BA and WCA were the best and fastest to find solutions. The PSO had slower results through all iterations, followed by the HS algorithm. The behavior of the four algorithms in finding the best solutions was similar for both cases presented in the figures.

Figures 7a and Fig 7b show the voltage magnitudes of the 33-node and 69-node radial distribution networks, respectively. The voltage magnitudes with no DGs and for the solutions found are presented in these figures for the purpose of locating five generators in both distribution networks.



(a)



(b)

Fig. 7. Voltage magnitudes for (a) the 33-node radial distribution network, and (b) the 69-node radial distribution network. Source: The authors

The solutions show that DG improves the voltage magnitudes of the nodes in the distribution networks. For both radial distribution networks, the voltage magnitudes improved with the solutions proposed by each algorithm, considering the voltage constraints. The WCA and HS found similar improvement of voltage magnitudes for most nodes of the 33-node radial distribution network, with a difference in nodes 19–25. For the 69-node radial distribution network, the solution of the WCA was different than the other algorithms, showing more improvement in nodes 51–65.

CONCLUSIONS

PSO, BA, HS, and a modified WCA were used to find the location and size of DG for two distribution networks. The tests performed in this research showed that the modified WCA obtained the minimum fitness in most cases after all scenarios and repetitions.

The evaluation of the algorithms' convergence was conducted with the average of the solutions found in the population, suggesting that the WCA is a good technique for finding solutions with few iterations and maintaining the good solutions until the end of the evaluations. The BA showed a good convergence to the best solutions, but the solutions were trapped in some local solutions and did not reduce after several iterations. The HS showed a slower convergence, but the WCA reached the best solutions for both distribution networks. The HS was faster with more numbers of nodes for all simulated scenarios. The PSO had some difficulty in improving the solutions with the number of iterations defined for the experiment.

The repetition tests show that the modified WCA found good results for all scenarios and similar minimum solutions after all iterations. These results demonstrate that this algorithm could provide the best solutions, independent of the number of repetitions conducted. Other algorithms such as the BA and HS found good results for most cases with a slight increase. The PSO provided some good solutions, especially for the smaller distribution network, but some solutions were high, especially for the larger distribution network.

REFERENCES

[1] L. Ramesh and S. Chowdhury, “Minimization of power Loss in distribution networks by different techniques,” Int. J. Electr. Electron. Eng., vol. 2, pp. 521–527, 2009.

[2] Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, and R. Seethapathy, “Optimal Renewable Resources Mix for Distribution System Energy Loss Minimization,” IEEE Trans. Power Syst., vol. 25, no. 1, pp. 360–370, Feb. 2010.

[3] D. Q. Hung, N. Mithulananthan, and R. C. Bansal, “Analytical strategies for renewable distributed generation integration considering energy loss minimization,” Appl. Energy, vol. 105, pp. 75–85, May 2013.

[4] D. Q. Hung, N. Mithulananthan, and R. C. Bansal, “Analytical Expressions for DG Allocation in Primary Distribution Networks,” IEEE Trans. Energy Convers., vol. 25, no. 3, pp. 814–820, Sep. 2010.

[5] D. D. Wu, M. Junjie, W. Yulong, and L. Yang, “Size and Location of Distributed Generation in Distribution System Based on Immune Algorithm,” Syst. Eng. Procedia, vol. 4, pp. 124–132, 2012.

[6] D. Zhang, Z. Fu, and L. Zhang, “Joint Optimization for Power Loss Reduction in Distribution Systems,” IEEE Trans. Power Syst., vol. 23, no. 1, pp. 161–169, Feb. 2008.

[7] G. N. S, D. K. Khatod, and M. P. Sharma, “Optimal Allocation of Distributed Generation in Distribution System for Loss Reduction,” vol. 28, pp. 42–46, 2012.

[8] a. K. Singh and S. K. Parida, “Selection of load buses for DG placement based on loss reduction and voltage improvement sensitivity,” 2011 Int. Conf. Power Eng. Energy Electr. Drives, no. May, pp. 1–6, May 2011.

[9] Y.-K. Wu, C.-Y. Lee, L.-C. Liu, and S.-H. Tsai, “Study of Reconfiguration for the Distribution System With Distributed Generators,” IEEE Trans. Power Deliv., vol. 25, no. 3, pp. 1678–1685, Jul. 2010.

[10] R. S. Rao, K. Ravindra, K. Satish, and S. V. L. Narasimham, “Power Loss Minimization in Distribution System Using Network Reconfiguration in the Presence of Distributed Generation,” IEEE Trans. Power Syst., vol. 28, no. 1, pp. 317–325, Feb. 2013.

[11] M. P. Lalitha, V. C. V. Reddy, and V. Usha, “Optimal DG Placement for Minimum Real Power Loss in Radial Distribution Systems using PSO,” J. Theor. Appl. Inf. Technol., vol. 13, no. 2, pp. 107 – 116, 2010.

[12] S. Kansal, B. B. R. Sai, B. Tyagi, and V. Kumar, “Optimal placement of distributed generation in distribution networks,” Int. J. Eng. Sci. Technol., vol. 3, no. 3, pp. 47 – 55, 2011.

[13] M. Mohammadi and M. A. Nasab, “PSO Based Multiobjective Approach for Optimal Sizing and Placement of Distributed Generation,” Res. J. Appl. Sci. Eng. Technol., vol. 2, no. 8, pp. 832–837, 2011.

[14] A. M. El-Zonkoly, “Optimal placement of multi-distributed generation units including different load models using particle swarm optimization,” Swarm Evol. Comput., vol. 1, no. 1, pp. 50–59, Mar. 2011.

[15] L. Wang and C. Singh, “Reliability-Constrained Optimum Placement of Reclosers and Distributed Generators in Distribution Networks Using an Ant Colony System Algorithm,” IEEE Trans. Syst. Man, Cybern. Part C (Applications Rev., vol. 38, no. 6, pp. 757–764, Nov. 2008.

[16] B. Sookananta, P. Utaton, and R. Khongsila, “Determination of the optimal location and sizing of Distributed Generation using Ant Colony Search,” in International Conference on Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON), 2010, pp. 814–817.

[17] C. L. T. Borges and D. M. Falcão, “Optimal distributed generation allocation for reliability, losses, and voltage improvement,” Int. J. Electr. Power Energy Syst., vol. 28, no. 6, pp. 413–420, Jul. 2006.

[18] G. Celli, E. Ghiani, S. Mocci, and F. Pilo, “A Multiobjective Evolutionary Algorithm for the Sizing and Siting of Distributed Generation,” IEEE Trans. Power Syst., vol. 20, no. 2, pp. 750–757, May 2005.

[19] M. F. Shaaban, Y. M. Atwa, and E. F. El-Saadany, “DG Allocation for Benefit Maximization in Distribution Networks,” IEEE Trans. Power Syst., vol. 28, no. 2, pp. 1–1, May 2012.

[20] T. Sutthibun and P. Bhasaputra, “Multi-objective optimal distributed generation placement using simulated annealing,” in Internacional Conference on Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON), 2010, pp. 810–813.

[21] A. I. Aly, Y. G. Hegazy, and M. A. Alsharkawy, “A simulated annealing algorithm for multi-objective distributed generation planning,” in IEEE PES General Meeting, 2010, pp. 1–7.

[22] N. Ghadimi and R. Ghadimi, “Optimal Allocation of Distributed Generation and Capacitor Banks in Order to Loss Reduction in Reconfigured System,” Res. J. Appl. Sci. Eng. Technol., vol. 4, no. 9, pp. 1099 – 1104, 2012.

[23] J. E. Candelo and H. E. Hernández, “Location and Size of Distributed Generation to Reduce Power Losses using a Bat-inspired Algorithm,” in VII Simposio Internacional sobre Calidad de la Energía Eléctrica, 2013.

[24] J. E. Candelo and H. E. Hernández, “Distributed Generation Placement in Radial Distribution Networks using a Bat-inspired Algorithm,” Dyna-Colombia, 2015.

[25] A. Parizad, A. H. Khazali, and M. Kalantar, “Sitting and sizing of distributed generation through Harmony Search Algorithm for improve voltage profile and reducuction of THD and losses,” in CCECE 2010, 2010, pp. 1–7.

[26] K. S. Rao and M. N. Rao, “Multiple distributed generator allocation by Harmony search algorithm for loss reduction,” in 2012 International Conference on Emerging Trends in Electrical Engineering and Energy Management (ICETEEEM), 2012, pp. 59–64.

[27] J. E. Candelo and H. E. Hernández, “Location and Size of Distributed Generation to Reduce Power Losses using a Bat-inspired Algorithm,” in VII Simposio Internacional sobre Calidad de la Energía Eléctrica, 2013.

[28] H. Eskandar, A. Sadollah, A. Bahreininejad, and M. Hamdi, “Water cycle algorithm - A novel metaheuristic optimization method for solving constrained engineering optimization problems,” Comput. Struct., vol. 110–111, pp. 151–166, 2012.

[29] H. Manafi, N. Ghadimi, M. Ojaroudi, and P. Farhadi, “Optimal Placement of Distributed Generations in Radial Distribution Systems Using Various PSO and DE Algorithms,” Elektron. IR ELEKTROTECHNIKA, vol. 19, no. 10, pp. 53–57, 2013.

[30] X.-S. Yang, “A New Metaheuristic Bat-Inspired Algorithm,” in Nature Inspired Cooperative Strategies for Optimization (NICSO 2010) SE - 6, vol. 284, J. González, D. Pelta, C. Cruz, G. Terrazas, and N. Krasnogor, Eds. Springer Berlin Heidelberg, 2010, pp. 65–74.
[31] J. D. Altringham, Bats: Biology and Behaviour. Oxford University Press, 1997.
[32] Zong Woo Geem, Joong Hoon Kim, and G. V. Loganathan, “A New Heuristic Optimization Algorithm: Harmony Search,” Simulation, vol. 76, no. 2, pp. 60–68, 2001.
[33] S. A. Taher and S. A. Afsari, “Optimal location and sizing of UPQC in distribution networks using differential evolution algorithm,” Math. Probl. Eng., vol. 2012, 2012.
[34] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” IEEE Trans. Power Deliv., vol. 4, no. 2, pp. 1401–1407, Apr. 1989.
[35] P. Phonrattanasak and N. Leeprechanon, “Optimal Location of Fast Charging Station on Residential Distribution Grid - Volume 3 Number 6 (Dec. 2012) - IJIMT,” Int. J. Innov. Manag. Technol., vol. 3, no. 6, pp. 675–681, 2012.