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# A hybrid bat-inspired algorithm with harmony search to locate distributed generation

## Un híbrido del algoritmo inspirado en murciélagos y el algoritmo basado en búsqueda armónica para la ubicación de generación distribuida

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**Content**



**ABSTRACT:**
The use of distributed generation (DG) is an important strategy of electricity companies to improve the power losses in distribution networks. This paper proposes a hybrid algorithm based on the bat-inspired algorithm (BA) and the harmony search algorithm (HS) to avoid premature convergence. The results showed that the new hybrid algorithm has the advantage of converging quickly to the best solutions and finds better solutions through a combination of the best positions of individuals.
**key words** bat-inspired algorithm, distributed generation, harmony search, metaheuristic algorithms.

**RESUMEN:**
El uso de Generación Distribuida (GD) es una importante estrategia de las compañías eléctricas para mejorar las pérdidas de potencia en sus redes de distribución. Este artículo propone un algoritmo híbrido basado en el algoritmo inspirado en murciélagos y en el algoritmo de búsqueda armónica que evita la convergencia prematura. Los resultados obtenidos muestran que el nuevo algoritmo tiene como ventajas que converge rápidamente hacia las mejores soluciones y que encuentra soluciones de buena calidad.
**Palabras clave** Algoritmo inspirado

# 1. Introduction

Power losses represent a major problem for the energy efficiency of distribution networks and distribution system operators (DSOs) must deal with the improvement to avoid higher operating cost. A reduction in the power losses in a distribution network is beneficial to improve power transfer, voltage magnitudes, power quality, and voltage stability.

DSOs have several alternatives for facing the energy losses. Some of the best options include the use of DG (Atwa, El-Saadany, Salama, & Seethapathy, 2010; Hung, Mithulananthan, & Bansal, 2010, 2013; Naik, Khatod, & Sharma, 2012; Singh & Parida, 2011; D. D. Wu, Junjie, Yulong, & Yang, 2012; Zhang, Fu, & Zhang, 2008), capacitor placement (Ramesh & Chowdhury, 2009; Singh & Parida, 2011), feeder restructuring (Ramesh & Chowdhury, 2009), and network reconfiguration (R. S. Rao, Ravindra, Satish, & Narasimham, 2013; Y.-K. Wu, Lee, Liu, & Tsai, 2010). DG is widely used because of the amount of energy supplied close to the loads, which allows improvement of the operating conditions of the network. DG can be financed by the DSO, the investor, or the final users, and the decision must be supported by the electricity-market regulation in each country.

The development of the DG in many countries allows final users to install sources, but doing so decreases the requested load in the network and is normally conceived for economics' sake. However, this method is not focused on improving the electrical network and its operation, since the load reduction is performed at some points of the network with no optimization process. Thus, it is preferable that electricity companies select the best points to install the new generators, supporting better use of the energy resources.

The implementation of DG by the DSO or the investors is a good option to maintain better conditions in the network. The experimental results of the method have shown that it is useful for the network; therefore, it should be prioritized for the development of power grids and to obtain better reliability in the electricity service. For that reason, this research proposes an algorithm that finds the best location for DG to develop the power grid by means of the DSO or the investors. For some countries, implementing the solution must lead to some changes in the regulation of the electricity market, especially the roles of the participants.

The installation of the DG in the distribution network benefits participants in the electricity market. The DSO has more availability in the network, less congestion, greater reliability, better power quality, etc. Generation investors would be able to participate in the production of electricity closer to the users. The retailer would have more options for purchasing electricity, which means lower prices and achieving greater competitiveness in the market. Users will have options for reducing the costs of electricity, and they also can coordinate with the DSO, investors, and retailers to install DG and improve the availability of electricity.

Determining the best location and size of DG using exact techniques can be a time-consuming computation. Metaheuristic algorithms are generally robust techniques that provide near-optimal solutions for this type of problem (Georgilakis & Hatziargyriou, 2013). Several metaheuristics have been tested to solve this problem (Tan, Hassan, Majid, & Abdul Rahman, 2013), such as the particle swarm optimization (PSO) (El-Zonkoly, 2011; Kansal, Sai, Tyagi, & Kumar, 2011; Lalitha, Reddy, & Usha, 2010; Mohammad & Nasab, 2011), ant colony (AC) (Sookananta, Utaton, & Khongsila, 2010; L. Wang & Singh, 2008), evolutionary algorithm (EA) (Borges & Falcão, 2006; Celli, Ghiani, Mocci, & Pilo, 2005; Shaaban, Atwa, & El-Saadany, 2012), simulated annealing (SA) (Aly, Hegazy, & Alsharkawy, 2010; Ghadimi & Ghadimi, 2012), and BA (Candelo Becerra & Hernández Riaño, 2015), HS (Parizad, Khazali, & Kalantar, 2010; K. S. Rao & Rao, 2012). These algorithms do not guarantee an optimal solution for the problem studied. Therefore, researchers are continually searching for the best algorithms to solve each problem.

One of the most important algorithms recently tested to solve this problem was the BA, obtaining good results when locating and sizing the DG, but several convergence problems have been detected when trying to solve difficult problems (Candelo Becerra & Hernández Riaño, 2015). The advantage of this technique is the fast movements of the individuals to the best location, but a search of the best solutions can be limited according to the solutions found near the optimum, requiring the testing of other combinations to avoid convergence problems.

Another important algorithm is the HS, with the capacity to generate a new solution vector after considering all vectors previously obtained as solutions. The algorithm combines good solutions found during different iterations, increasing the flexibility and capacity to obtain better solutions (Mahdavi, Fesanghary, & Damangir, 2007).

Therefore, this research proposed a new BA with HS for searching the best solutions to find the location and size of the DG and for improving the search of different cases. The combinations of these techniques are reported as good results for numerical problems (G. Wang & Guo, 2013), but their effectiveness in applications for electrical engineering and the implementation of better techniques according to the problem are needed.

The development of hybrid metaheuristic algorithms is an important issue for determining the best location and size of DG. For that reason, some researchers have focused on developing new techniques to improve the search (Evangelopoulos & Georgilakis, 2014; Kollu, Rao Rayapudi, & Narasimham Sadhu, 2014; Yammani, Maheswarapu, & Kumari Matam, 2015).

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# 2. Problem formulation

The model presented in this research seeks to represent the problem of power losses in distribution networks from the point of view of the electricity companies, where DG is used to reduce power losses (Manafi, Ghadimi, Ojaroudi, & Farhadi, 2013).

## 2.1. Power Losses

Although losses are normally classified into technical and commercial (Antmann, 2009), this work focuses on the study of technical losses. Power losses in a distribution network are calculated as expressed in (1) (Manafi et al., 2013).

$$O.F.=\sum_{i=1}^{n}\sum_{j=1}^{n}A_{ij}(P_iP_j+Q_iQ_j)+B_{ij}(Q_iP_j+P_iQ_j) \qquad (1)$$

where $A_{ij}=\frac{R_{ij}\cos(\delta_i-\delta_j)}{V_iV_j}$ and $B_{ij}=\frac{R_{ij}\sin(\delta_i-\delta_j)}{V_iV_j}$. $P_i$ and $Q_i$ are the real and reactive power injected to the bus $i$, respectively. $P_j$ and $Q_j$ are the real and reactive power injected to the bus $j$, respectively. $R_{ij}$ is the resistance between the buses $i$ and $j$. $V_i$ and $\delta_i$ are the voltage magnitude and the voltage angle of the bus $i$, respectively. $V_j$ and $\delta_j$ are the voltage magnitude and the voltage angle of the bus $j$, respectively.

## 2.2. Power Flow Balance

The real power balance of the network is defined as in (2).

$$P_{Slack}+\sum_{i=1}^{n}P_{DGi}=\sum_{i=1}^{n}P_{Di}+P_L \qquad (2)$$

where $P_{Slack}$ is the real power of the slack bus, $P_{DGi}$ is the real power of the generator located at the bus $i$, $P_{Di}$ is the real power of the load located at bus $i$, and $P_L$ is the real power losses of the network.
The reactive power balance of the network is defined in (3).

$$Q_{Slack}+\sum_{i=1}^{n}Q_{DGi}=\sum_{i=1}^{n}Q_{Di}+Q_L \qquad (3)$$

where $Q_{Slack}$ is the reactive power of the slack bus, $Q_{DGi}$ is the reactive power of the DG located at the bus $i$, $Q_{Di}$ is the reactive power of the load located at bus $i$, and $Q_L$ is the reactive power losses of the network.

## 2.3. Voltage limits

Voltage magnitudes must be controlled at each bus of the distribution networks to prevent damage to the user's equipment. For this reason, the upper and lower voltage bounds are defined as shown in (4).

$$|V_i|^{\min} \leq |V_i| \leq |V_i|^{\max} \quad (4)$$

where $|V_i|$ is the voltage magnitude of bus *i*, $|V_i|^{\min}$ is the minimum voltage magnitude accepted for the bus *i*, and $|V_i|^{\max}$ is the maximum voltage magnitude accepted for the bus *i*. Each solution selected by the optimization technique must comply with the voltage limits of all nodes when the generators are located.

## 2.4. Branch currents limits

To avoid overloads on elements connected in series, the current constraints were considered in the optimization algorithms. Therefore, each branch will have the definition of the maximum current, as shown in (5) y (6).

$$I_{ij} \leq I_{ij}^{Max} \quad (5)$$

$$I_{ji} \leq I_{ji}^{Max} \quad (6)$$

$I_{ij}$ is the current supplied from node *i* to node *j*, and $I_{ji}$ is the current supplied from node *j* to node *i*. $I_{ij}^{Max}$ and $I_{ji}^{Max}$ are the maximum line currents from buses *i* to *j* and *j* to *i*, respectively. The algorithm used to find the solutions will include the constraints defined in these equations and will ensure that the selected installation of the distributed generation solutions complies with the boundaries.

## 2.5. Real and reactive power limit of DG

The power supplied by the distributed generation is limited by the minimum and maximum values, therefore, real power limits are defined as in (7) and reactive power limits are defined in (8).

$$P_{DGi}^{min} \leq P_{DGi} \leq P_{DGi}^{max} \quad (7)$$

$$Q_{\mathrm{DGi}}^{\min} \leq Q_{DGi} \leq Q_{\mathrm{DGi}}^{\max} \quad (8)$$

where $P_{\mathrm{DGi}}$ is the real power of distributed generation located at bus *i*, $P_{\mathrm{DGi}}^{\min}$ is the minimum real power of distributed generation located at bus *i*, and $P_{\mathrm{DGi}}^{\max}$ is the maximum real power of distributed generation located at bus *i*. $Q_{\mathrm{DGi}}$ is the reactive power of distributed generation located at bus *i*, $Q_{\mathrm{DGi}}^{\min}$ is the minimum reactive power of distributed generation located at bus *i*, and $Q_{\mathrm{DGi}}^{\max}$ is the maximum reactive power of distributed generation located at bus *i*.

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# 3. Metaheuristic algorithms

The BA and HS techniques have exhibited a good performance in different engineering problems. However, for the location and size of the DG, the algorithms have shown difficulties in finding better solutions, especially for several generators. Therefore, we propose the use of the CBAHS to determine better solutions in a reduced number of iterations.

## 3.1. Encoding

For the implementation of the algorithms, the problem was encoded as shown in Figure 1. This codification represents the location and size of distributed generators. Each individual or particle inside the algorithm corresponds to a solution of the problem.

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

**Figure 1**
Problem codification for location and size of distributed generators.

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $x_1$ | $y_1$ | $z_1$ | $x_2$ | $y_2$ | $z_2$ | ... | $x_d$ | $y_d$ | $z_d$ | ... | $x_{nd}$ | $y_{nd}$ | $z_{nd}$ |

## 3.2. Bat-inspired Algorithm

This algorithm was first presented by (Yang, 2010), and it is based on the echolocation of bats during the search for a prey. The algorithm starts with an initial population and moves all bats using the frequency and velocity. The use of random flies helps in finding new solutions in the searching region. The steps implemented in this work were programmed in the Matlab software as follows:

1) Initialize the population of bats and the velocities $v_i$.
2) Define the frequency $f_i$, pulse rate $r_i$ and loudness $A_i$.
3) Calculate the fitness for each bat.
4) Rank the solutions and select the best positioned and the fitness $F_{best}$
5) While $iter < iter_{max}$
   a. Generate new solutions $x_{new}$ by adjusting the frequency $f_i$ and velocities $v_i$ of the bats
   b. If $rand > r_i$
      - Generate a solution close to the best solution
   c. End if
   d. Generate new solutions with random flies of bats
   e. Calculate the new fitness $F_{new}(x_{new})$
   f. if ($F_{new}<F_{best}$ and rand$<A_i$)
      - Update solution
   g. End if
   h. Increase $r_i$ and reduce $A_i$
   i. Rank the solutions and select the best positioned and the fitness $F_{best}$
6) End while

The frequency and the velocity are calculated using (9) and (10), respectively.

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \qquad (9)$$

$$v_i^{k+1} = v_i^k + (x_i^k - x_{best})f_i \qquad (10)$$

where, $f_{min}$ is the minimum frequency, $f_{max}$ is the maximum frequency and $\beta$ is a random number with uniform distribution. $v_i^{k+1}$ is the new velocity of each bat $i$, $v_i^k$ is the previous velocity, $x_i^k$ is the current position of each bat and $x_{best}$ is the best position of bats.

The new position of each bat, $x_i^{k+1}$, is obtained using the current position of each bat, $x_i^k$, and the new velocity of each bat, $v_i^{k+1}$, as shown in (11).

$$x_i^{k+1} = x_i^k + v_i^{k+1} \qquad (11)$$

The advantage of this algorithm is the fast convergence to a solution because the individuals follow the best positioned (Candelo Becerra & Hernández Riaño, 2015).

## 3.3. Harmony Search

This algorithm was first proposed by (Zong Woo Geem, Joong Hoon Kim, & Loganathan, 2001) in 2001, and it is based on the improvisation made by musicians when playing instruments. The steps of the algorithm are described as follows:

1) Define the parameters
2) Initialize the population in the vector *HM*
3) Rank the solutions and select the best positioned and the fitness $F_{best}$
4) While $iter < iter_{max}$
   a. Generate new solutions $x_{new}$
   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 advantage of this algorithm is the combination of different solutions with the use of a vector created from the best individuals. Several combinations help the search for the best value found. The time needed for the combinations could be a disadvantage of the algorithm when applying it to power systems.

## 3.4. Hybrid BA with random HS flies

The hybridization of the algorithms is conducted to improve the search of the objective function by flying randomly using a harmony search combination. The steps implemented in the algorithm were based on (G. Wang & Guo, 2013).

1) Initialize the population of the bats and velocities.
2) Define the frequency $f_i$, pulse rate $r_i$, loudness $A_i$, and initialize the vector *HM*
3) Calculate the fitness for each bat.
4) Rank the solutions and select the best positioned and the fitness $F_{best}$
5) While $iter < iter_{max}$
   a. Generate new solutions $x_{new}$ by adjusting the frequency and velocities of the bats
   *b.* If $rand > r_i$
      - Generate a solution close to the best solution
   c. End if
   d. If *rand > flies*
      - Generate new solutions using the bats by flying with Harmony Search
   e. End if
   f. Calculate the new fitness $F_{new}(x_{new})$
   g. if ($F_{new}<F_{best}$ and $rand< A_i$)
      - Update solution
   h. End if
   *i.* Increase $r_i$ and reduce $A_i$
   *j.* Rank the solutions and select the best positioned with their fitness $F_{best}$
6) End while

The frequency, the velocity and the new position of bats are calculated using (9), (10) and (11), respectively. The advantage of this hybrid algorithm is the inclusion of the harmony search to generate random solutions close to the best solutions.

## 3.5. Hybrid BA with HS convergence

The hybridization of these algorithms is conducted to improve the convergence towards solutions when the combinatorial problems become more difficult. The best characteristics of the BA and HS were combined to improve the search for a fast combinatorial solution. BA conducts the main search to take advantage of its high speed of convergence, and HS is activated only when the search has been trapped in a local optimum. Reactivation of the initial algorithm BA is conducted when a new good solution is found using the HS and the cycle repeat until the last iteration. This combination of algorithms was performed to obtain a fast hybrid algorithm with the possibility to escape from local optimal solutions when solving the problem of locating and sizing distributed generation.

The steps implemented in the algorithm are described as follows:

1) Initialize the population of bats and their velocities.
2) Define the frequency $f_i$, pulse rate $r_i$, loudness $A_i$, initialize the vector *HM*, and activate the BA search.
3) Calculate the fitness for each bat.
4) Rank the solutions and select the bests positioned and the fitness $F_{best}$
5) While $iter < iter_{max}$
   a. If the BA is active
      - Generate new solutions $x_{new}$ by adjusting the frequency and the velocities of the bats
   b. Else if the HS is active
      - Generate new solutions $x_{new}$ by combining the solutions
   c. End if
   d. If $rand > r_i$
      - Generate a solution close to the best solution
   e. End if
   f. If *rand>flies*
      - Generate new solutions by flying with the HS
   g. End if
   h. Calculate the new fitness $F_{new}(x_{new})$
   i. if ($F_{new}<F_{best}$ and $rand<A_i$)
      - Update solution
   j. End if
   k. Increase $r_i$ and reduce $A_i$
   l. Rank the solutions and select the best positioned with their fitness $F_{best}$
   m. If ($\Delta avg < \varepsilon$)
      - $x_c = x_c + 1$
      - If $x_c > x_{cmax}$
        1. Generate a solution close to the best solution
        2. Activate harmony search
   n. End if
   o. Else
      - $x_c = 0$
      - Activate bat-inspired search
   p. End if
6) End while

Where *xc* is the number of times that the average is smaller than the error and $x_{cmax}$ is the maximum number of successive iterations in $\Delta avg$ that is smaller than the error $\varepsilon$. The frequency, the velocity and the new position of bats are calculated using (9), (10) and (11), respectively.

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# 4. Test system and simulation

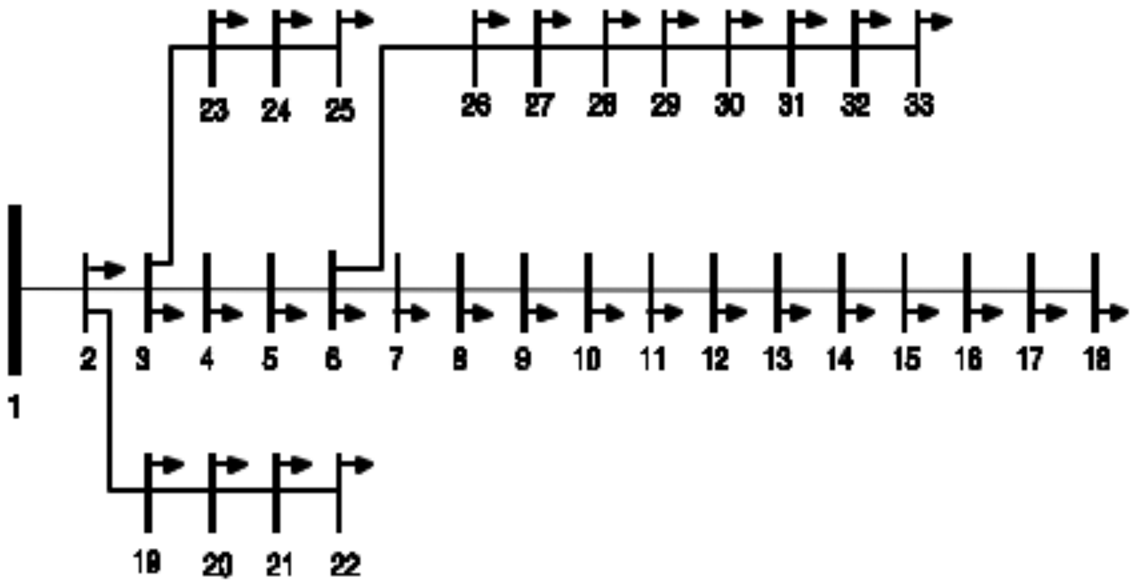
## 4.1. Test System Cases

To test the proposed metaheuristic, two balanced distribution network were used. The 33-node and 69-node radial distribution networks are standard cases used to test the location and size of the DG.

## 4.2. Case 33-node radial distribution network

This distribution network has 33 nodes with one feeder at node 1 and 32 loads for the rest of the system (Baran & Wu, 1989; Taher & Afsari, 2012). Figure 2 shows the diagram of the 33-node radial distribution network.

**Figure 2**
Case 33-node radial distribution network. Source:(Taher & Afsari, 2012).

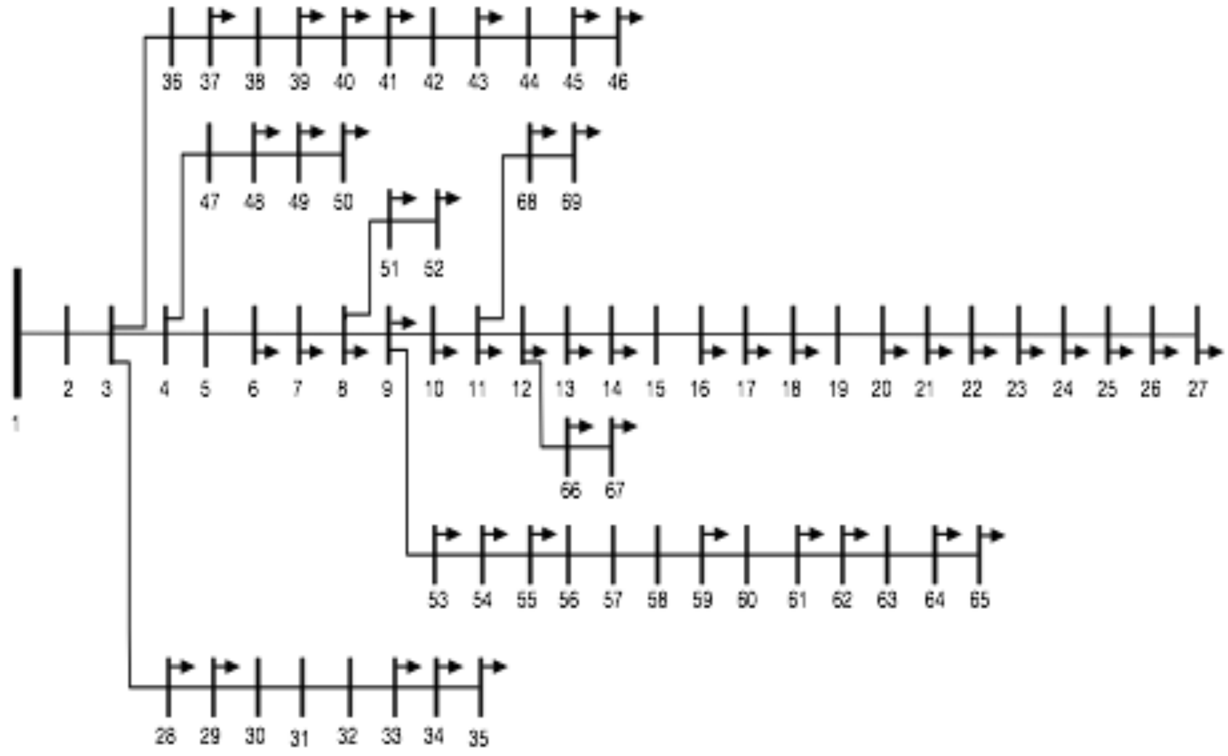



Case 33-node radial distribution network has a total load of 3715 kW and 2300 kVAr and a total supply of 3926 kW and 2443 kVAr. The voltage limits at the load buses were defined as *Vmin*=0.9 p.u. and *Vmax*=1.1 p.u. The possible nodes to locate the DG were selected according to the definition of the PQ nodes, providing a total of 32 nodes.

## 4.3. Case 69-node radial distribution network

This distribution network has 69 nodes with one feeder at node 1 and 49 loads as shown in Figure 3 (Phonrattanasak & Leeprechanon, 2012; Taher & Afsari, 2012). This distribution network has a total load of 4014 kW and 2845 kVAr and a total generation 4265 KW and 2957 kVAr. The voltage limits at the load buses were considered as 10% of the rated voltage or *Vmin*=0.9 p.u. and *Vmax*=1.1 p.u. The possible nodes for locating the DG were selected according to the definition of the PQ nodes, providing a total of 68 nodes.

**Figure 3**
Case 69-node radial distribution network. Source:(Taher & Afsari, 2012).




## 4.4. Scenarios for the simulation

The simulation scenarios presented in this study aimed to evaluate the performance of the proposed algorithm. Variations in the number and size of DG were performed to find the best location in the distribution network to supply electricity to the different levels of demand. The selection of the power system cases, the design of the simulations scenarios, and the determination of the parameters of operation, including in the algorithms, were carried out as described in the literature and in previous works published by the authors of the present study.

Previous research has determined that the location and size of a few generators and lower capacities are not a problem for metaheuristics with a small number of individuals and iterations (Candelo Becerra & Hernández Riaño, 2015). Because a large number of generators and capacities showed different results, this paper focuses on the search for better results with a hybrid BA-HS with generators changing from five to seven for the 33-node and 69-node radial distribution networks. The maximum power tested in (Candelo Becerra & Hernández Riaño, 2015) was used to compare all of the algorithms and to determine the best solutions. The power selected for each generator has a maximum real power of 2 MW with a power factor of 0.98 inductive.

The test consisted of obtaining similar characteristics for the four algorithms to evaluate the performance of each technique and determine the advantages. Comparisons of the minimum objective functions and the average of solutions were performed, considering the following parameters:

- The size of the population was defined as 1,000 individuals, because of the great diversity of the initial population and what the literature shows to be necessary to improve the performance of this type of algorithm.
- The stopping criteria of the algorithms was defined as 200 iterations.
- As the randomness of the initial population can provide advantages in finding good solutions for any of the algorithms, this problem was corrected for the experiment by using the same initial population. The algorithms start from the same population and begin to search for the best solution. This method was implemented with the aim of evaluating the performance of the algorithms through various iterations.
- Due to the stochastic nature of the algorithms, their performances were evaluated with the results of various tests. In this work, the comparison was made using five repetitions.

# 5. Results and discussion

## 5.1. Location and size results

Table 1 shows the results of the location and size of the DG using the four algorithms for the 33-node and 69-node radial distribution networks, respectively. The column *Case* corresponds to the power system test, *ng* is the number of generators, *Alg* is the algorithm used to determine the solution for each scenario, *Ptot* is the total active power supplied by the generators, *Nodes* is the node numbers that represent the solution with the minimum Fitness, *Fmin* is the minimum fitness, *Pfmin* is the ranking of the solution according to the minimum fitness, Favg is the average of the five solutions, and *Pfavg* is the ranking of the solution according to the minimum average.

**Table 1**
Location and size of the DG

| *Case* | *ng* | *Alg* | *Ptot* | *Nodes* | *Fmin* | *Pfmin* | *Favg* | *Pfavg* |
|---|---|---|---|---|---|---|---|---|
| 33-node case base | 0 | - | - | - | 210,9 | - | - | - |
| 33-node | 5 | BA | 3573 | 10-30-24-6-16 | 35,98 | 4 | 36,39 | 3 |
| | | HS | 3425 | 24-31-10-14-6 | 35,89 | 3 | 37,17 | 4 |
| | | SBAHS | 3453 | 11-24-6-31-16 | 35,57 | 2 | 35,75 | 2 |
| | | CBAHS | 3423 | 14-30-24-7-32 | 35,48 | 1 | 35,65 | 1 |
| | 6 | BA | 3440 | 24-15-11-7-32-30 | 34,41 | 3 | 35,13 | 3 |
| | | HS | 3054 | 12-7-30-14-25-31 | 35,87 | 4 | 36,58 | 4 |
| | | SBAHS | 3396 | 14-33-6-8-30-24 | 34,56 | 2 | 34,79 | 2 |
| | | CBAHS | 3299 | 10-32-16-7-25-30 | 34,42 | 1 | 34,74 | 1 |
| | 7 | BA | 3349 | 10-29-9-31-25-7-15 | 34,81 | 3 | 35,20 | 3 |
| | | HS | 3771 | 7-23-10-14-33-25-30 | 35,59 | 4 | 36,29 | 4 |
| | | SBAHS | 3720 | 16-10-6-21-29-24-31 | 33,37 | 2 | 33,92 | 2 |
| | | CBAHS | 3756 | 30-6-24-16-20-10-32 | 33,25 | 1 | 33,54 | 1 |
| 69-node case base | 0 | - | - | - | 265,0 | - | - | - |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 69-node | 5 | BA | 3747 | 61-54-18-21-50 | 38,78 | 4 | 40,28 | 4 |
| | | HS | 4120 | 49-23-12-61-8 | 37,34 | 3 | 37,64 | 2 |
| | | SBAHS | 3810 | 25-61-11-17-50 | 37,18 | 2 | 37,90 | 3 |
| | | CBAHS | 3925 | 61-23-11-64-50 | 36,99 | 1 | 37,19 | 1 |
| | 6 | BA | 6066 | 64-61-51-4-49-21 | 38,34 | 4 | 39,61 | 4 |
| | | HS | 4591 | 8-5-50-12-23-61 | 37,52 | 3 | 39,06 | 3 |
| | | SBAHS | 3886 | 68-61-17-23-50-25 | 37,35 | 2 | 38,09 | 2 |
| | | CBAHS | 3874 | 64-26-61-11-50-23 | 36,62 | 1 | 37,37 | 1 |
| | 7 | BA | 3376 | 61-64-16-11-21-38-63 | 38,81 | 4 | 38,96 | 3 |
| | | HS | 3403 | 21-3-24-67-49-13-61 | 39,31 | 3 | 40,32 | 4 |
| | | SBAHS | 4342 | 60-61-17-10-26-49-65 | 37,33 | 1 | 38,20 | 2 |
| | | CBAHS | 3757 | 16-61-22-10-35-49-64 | 37,43 | 2 | 37,54 | 1 |

*Favg* was considered a good indicator to measure the quality of the solutions, being the lower value the best solution found. Considering this indicator, the BA and HS algorithms obtained the worse solutions in 83% of the scenarios evaluated, demonstrating limitations in the solution for the problem studied. The BA found good solutions for problems with a small number of possible combinations as the 33-node radial distribution network and the HS found good results for difficult problems.

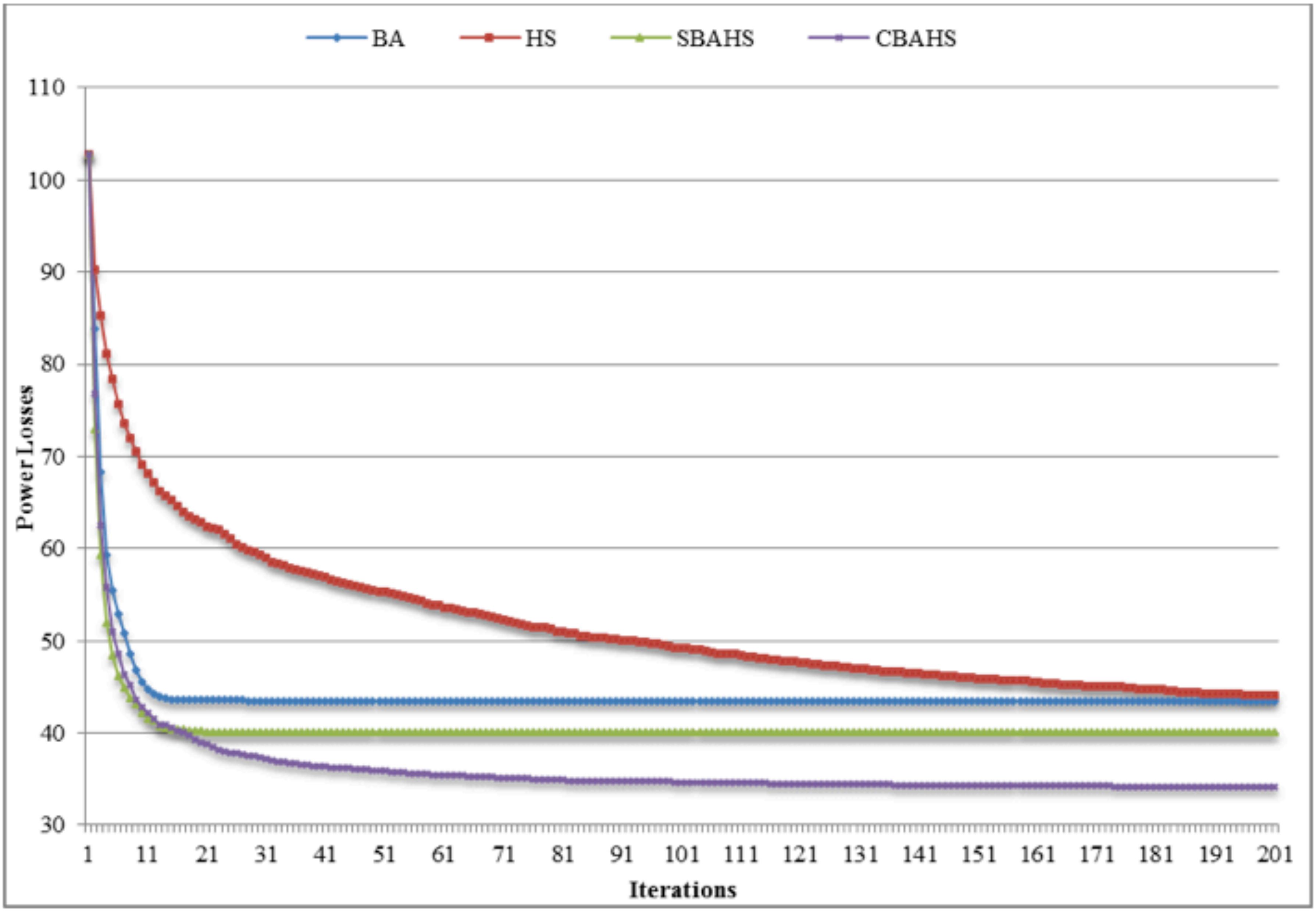
The hybrids SBAHS and CBAHS had better results for most cases compared to the solutions found with single algorithms. The SBAHS algorithm obtained good solutions in 83% of the scenarios evaluated, what represents a good performance for the problem studied. On the other hand, the CBAHS algorithm obtained the best solutions in 100% of the scenarios evaluated, considering different number and size of generators. The CBAHS obtained the minimum value of all repetitions and the best average of solutions, and we can conclude that it is the best method tested for finding the location and size of the DG.

On the other side, the location of DG in the 33-node radial distribution network impacted positively the energy efficiency of the network for all cases studied, obtaining an average reduction of 175.9 KW or 83.4% with respect to the base case. In the 69-node radial distribution network, the power losses reduced 227.2 KW or 85.7% with respect to the base case.

## 5.2. Convergence of the algorithms

Figure 4 shows the convergence of the three algorithms for the problem of locating and sizing six generators for scenario number 4. As a control of the experimental conditions, all algorithms considered the same initial population to avoid advantages with better random values and to evaluate the performance of the solutions during the iterations.

**Figure 4**
Convergence of the algorithms.




This figure shows that the BA is a method that rapidly found a good solution, reducing the fitness fast. As shown in the figure, the algorithm found a local solution and no improvement was seen during the other iterations.

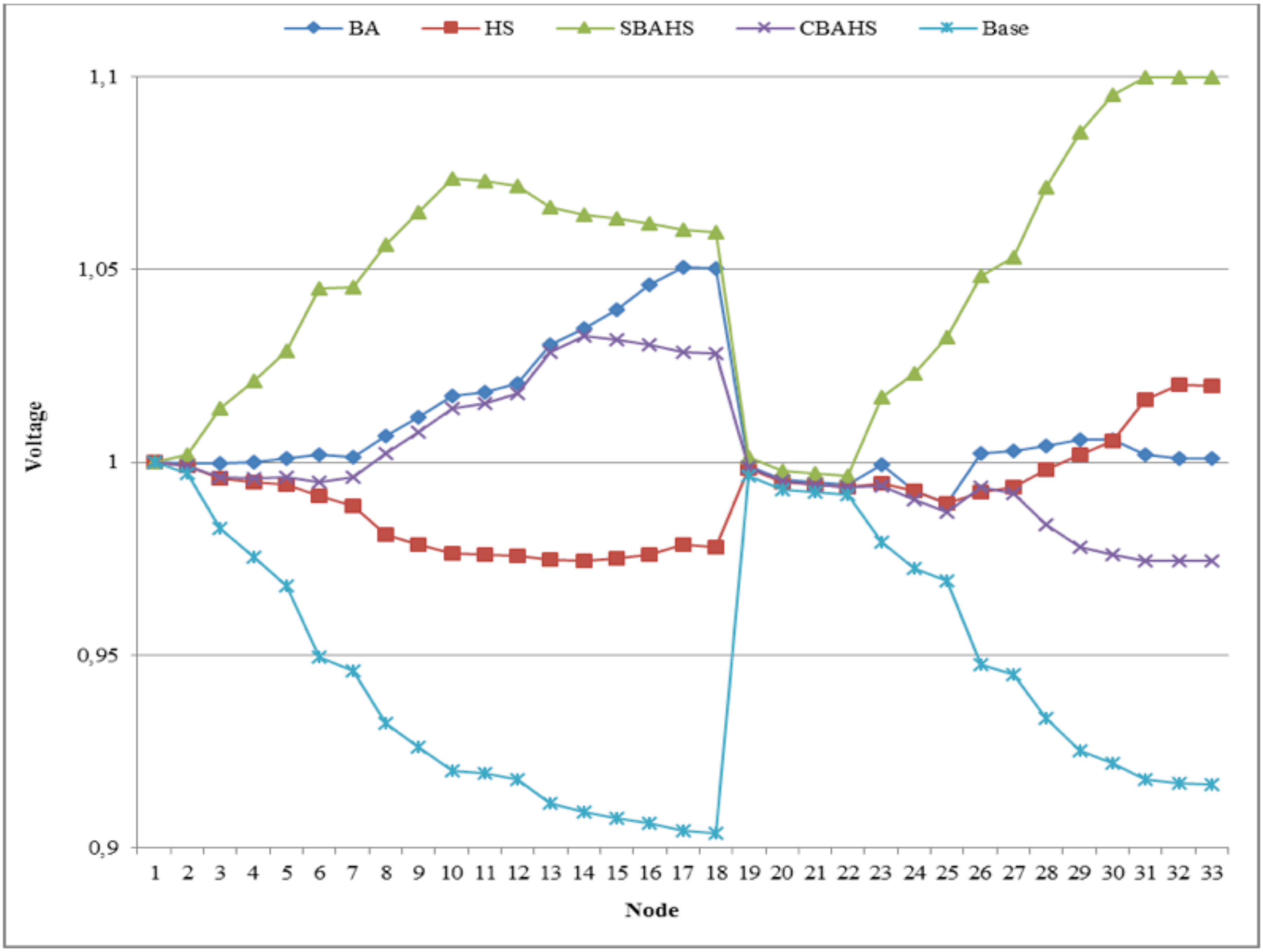
The HS found solutions with a slow reduction in the average fitness. Because the method is based on the combination of different solutions, the results were better for difficult problems. After several iterations, the location provided better results compared with the solution offered with the BA. In conclusion, the HS is a good method for locating the DG, but the time for solving problems must be improved.

The proposed hybrid technique allowed the fast convergence offered by the BA and the search for better solutions with the HS. The figure show that the BA starts obtaining good and fast results and after moving close to the convergence, the search with HS is activated, allowing better solutions. If a new and good solution is found, the search with the BA is reactivated until the new criteria reactivate the HS. This search was tested up to the final iteration. Better results were not found after several iterations.

For the analysis of the convergence for the studied algorithms, it is important to note that CBAHS does not present problems of premature convergence for the BA because of the high diversity of the solutions provided by the HS in the moments that the algorithm requires it. This implies that the resulting algorithm has a high speed of convergence combined with a high diversity of solutions.

Figure 5 shows the voltage magnitudes of the 33-node radial distribution network for the base case and the location of 5 generators with the different algorithms.

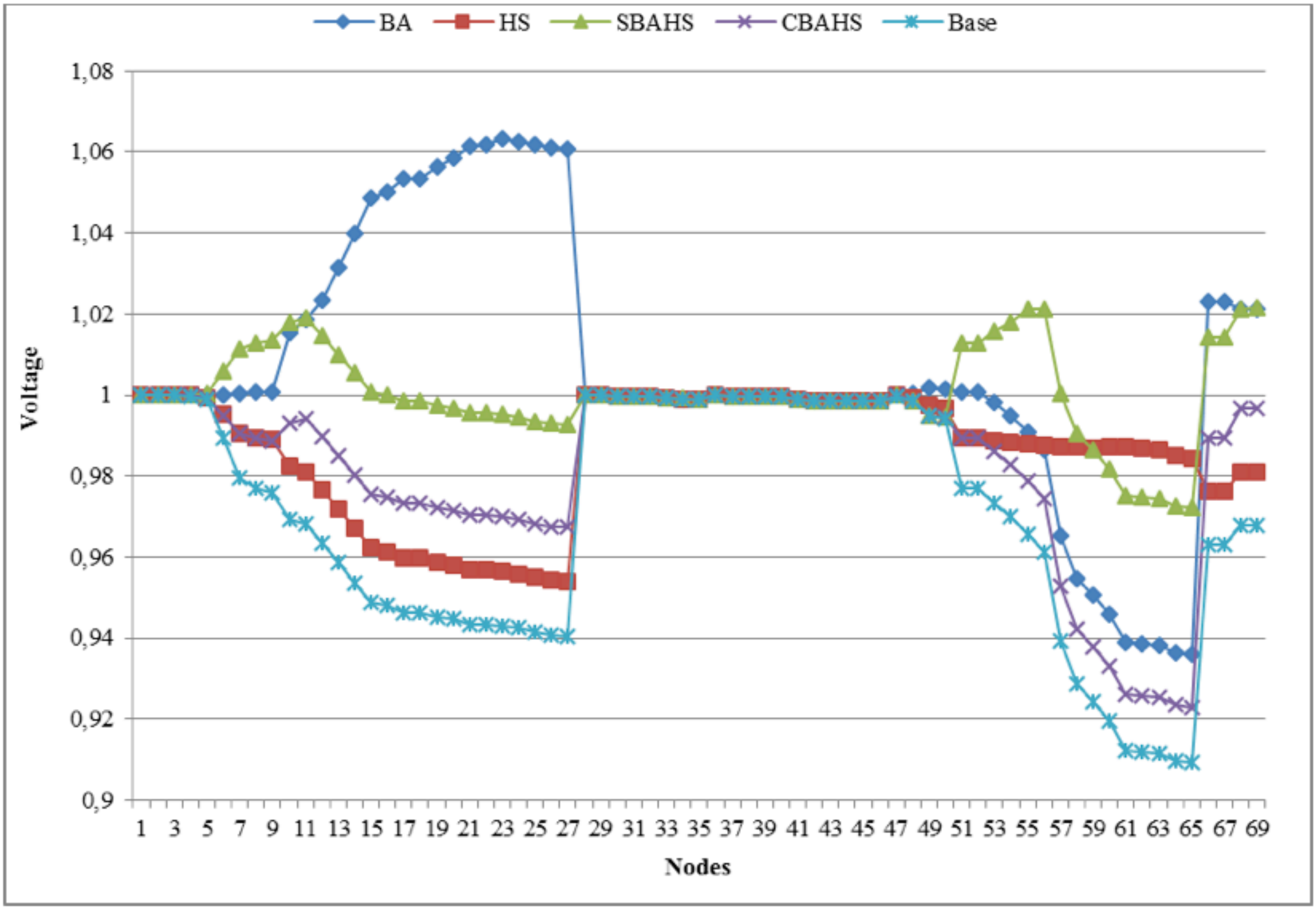
**Figure 5**
Voltage magnitudes of the 33-node radial distribution network.




Application of metaheuristic algorithms for the location and size of distributed generation allowed an improvement of voltage magnitudes of the 33-node radial distribution network. The SBAHS algorithm obtained higher voltage magnitudes than the other algorithms, but some magnitudes are close to the maximum limits. The HS algorithm improved more the voltage magnitudes of nodes from 26 to 33 and less of nodes from 14 to 19. The BA improved more the voltage magnitudes of nodes from 14 to 19 and nodes from 26 to 33. Although these algorithms improve the voltages in different way, the reduction of power losses were not the best for the distribution network. Nevertheless, the CBAHS improved more the voltage magnitudes of nodes from 7 to 18 and less the voltage magnitudes of nodes from 28 to 33, representing the best compensation of power from distribution network to reduce power losses.

Figure 6 shows the voltage profiles of the 69-node radial distribution network after using the 5 generators located for the scenario with the different algorithms.

**Figure 6**
Voltage magnitudes for the 69-node radial distribution network




Metaheuristic algorithms allowed an improvement of voltage magnitudes of the 69-node radial distribution network, but the solutions obtained different magnitudes. The BA improved more the voltage magnitudes of nodes from 12 to 27 and the SBAHS improved more the voltage magnitudes of nodes from 51 to 58. The HS improved more the voltage magnitudes of nodes from 56 to 66 and less the voltage magnitudes of nodes from 12 to 27. Although the different improvement in voltage magnitudes with these algorithm, the reduction of power losses were not the best for the distribution network. Nevertheless, the hybrid CBAHS increased voltage magnitudes for all the nodes in a moderate way, maintaining a distributed compensation to reduce power losses from the base case and the effect of increasing new power losses with the distributed generation installed.

# 6. Conclusions

The BA, HS, hybrid SBAHS and CBAHS were implemented in this work to find the best location of the DG in two radial distribution networks. The results show that the BA needed a small number of iterations to obtain good results, while the HS needed a large number of iterations to obtain similar results. The HS algorithm is a slower method but has the advantage of evaluating a key number of combinations. The SBAHS had good results for most cases, improving the solutions with the use of the random flies HS. The proposed CBAHS method had better results especially when testing difficult cases, which allows a lower reduction in power losses compared with the other three methods. A comparison of the four methods showed that the hybrid methods improved the results with a smaller number of populations and iterations, which reduces the calculation time for solving difficult problems. The results presented in this research seek to provide new algorithms for electricity companies that find better solutions when locating distributed generation to improve power losses.

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