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Comparison of multiobjective harmony search, cuckoo search and bat-inspired algorithms for renewable distributed generation placement

Comparación de algoritmos multiobjetivo inspirados en búsqueda armónica, búsqueda cuco y murciélagos para la ubicación de generación distribuida renovable

John E. Candelo-Becerra[1], Helman E. Hernández-Riaño[2] y Alcides R. Santander-Mercado[3]

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1 Ph.D. Electrical Engineer, Department of Electrical Energy and Automation, Universidad Nacional de Colombia - Sede Medellín, Medellín-Colombia, jecandelob@unal.edu.co
2 M.Sc. Industrial Engineer, Department of Industrial Engineering, Universidad de Córdoba, Montería-Colombia, hhernandez@correo.unicordoba.edu.co
3 Ph.D. Industrial Engineer, Department of Industrial Engineering, Universidad del Norte, Barranquilla-Colombia, asantand@uninorte.edu.co

Abstract

Electric power losses have a significant impact on the total costs of distribution networks. The use of renewable energy sources is a major alternative to improve power losses and costs, although other important issues are also enhanced such as voltage magnitudes and network congestion. However, determining the best location and size of renewable energy generators can be sometimes a challenging task due to a large number of possible combinations in the search space. Furthermore, the multiobjective functions increase the complexity of the problem and metaheuristics are preferred to find solutions in a relatively short time. This paper evaluates the performance of the cuckoo search (CS), harmony search (HS), and bat-inspired (BA) algorithms for the location and size of renewable distributed generation (RDG) in radial distribution networks using a multiobjective function defined as minimizing the energy losses and the RDG costs. The metaheuristic algorithms were programmed in Matlab and tested using the 33-node radial distribution network. The three algorithms obtained similar results for the two objectives evaluated, finding points close to the best solutions in the Pareto front. Comparisons showed that the CS obtained the minimum results for most points evaluated, but the BA and the HS were close to the best solution.

Keywords

Cuckoo search, bat-inspired algorithm, renewable distributed generation, harmony search, photovoltaic energy systems, wind energy systems.

Resumen

Las pérdidas eléctricas tienen un impacto significativo en los costos totales de las redes de distribución. El uso de las energías renovables es una gran alternativa para mejorar las pérdidas y los costos, aunque también otros problemas en las magnitudes de las tensiones y la congestión de la red pueden ser mejorados. Sin embargo, determinar la mejor localización y dimensionamiento de generadores eléctricos renovables puede ser a veces una tarea difícil debido al gran número de combinaciones posibles existentes en el espacio de búsqueda. Además, el uso de funciones multiobjetivo incrementa la complejidad del problema y se prefiere usar las metaheurísticas para encontrar soluciones en un tiempo relativamente corto. En este trabajo se evalúa el desempeño de los algoritmos inspirados en búsqueda cuco, búsqueda armónica y murciélagos para la localización y dimensionamiento de la generación distribuida renovable en redes de distribución radiales, usando funciones como la minimización de las pérdidas de energía y los costos de la generación distribuida renovable. Las metaheurísticas fueron programadas en Matlab y evaluadas usando la instancia denominada red de distribución radial de 33 nodos. Los tres algoritmos evaluados obtuvieron resultados similares para los dos objetivos evaluados, encontrando Frentes de Pareto cercanos a las mejores soluciones. La comparación realizada mostró que la búsqueda cuco obtiene los mejores resultados, pero los algoritmos inspirados en murciélagos y búsqueda armónica obtuvieron resultados cercanos a la mejor solución.

Palabras clave

Búsqueda cuco, búsqueda armónica, algoritmo inspirado en murciélagos, generación distribuida renovable, sistemas fotovoltaicos, sistemas eólicos.

1. INTRODUCTION

Power losses cause energy efficiency issues for distribution networks and reflect in unwanted costs of operation for electricity distribution companies. Some of the solutions proposed in literature are network reconfiguration [1], [2]; feeder restructuring [3]; capacitor placement [3]; and distributed generation (DG) [4]-[10].

Renewable energies are important power sources that help to reduce power losses of distribution networks; to enhance voltage magnitudes, power quality, and network congestion; and to solve other problems. Location of renewable distributed generation (RDG) is a good option to reduce power losses, but due to the combinatorial nature of the problem, the conventional or classical optimization techniques such as branch and bound require large computation capacities for the solution of large networks [11].

Currently, there are many metaheuristic algorithms oriented to the optimization and solution of engineering problems. These algorithms have solved problems in the fields of mathematics; mechanical, electronic, and electrical engineering; and others. Some of the most common algorithms studied and implemented are firefly algorithm (FA), artificial bee colony (ABC), particle swarm optimization (PSO), cuckoo search (CS), bat-inspired algorithm (BA), and harmony search (HS).

The HS, CS, and BA are algorithms recently tested to solve different problems in engineering. The HS algorithm has the capacity to generate new solutions considering previous selected solutions in a vector, offering a good number of combinations to increase the flexibility and capacity to obtain better solutions [12], an advantage for locating DG [13], [14]. The CS has been applied to optimize power losses [15] and is also useful for improving energy efficiency and operation costs. The BA has also been applied to solve the problem of locating and sizing DG, obtaining good results [16].

This article focuses on evaluating the performance of the CS, BA, and HS for finding the location and size of RDG in distribution networks. Therefore, a multiobjective function defined as minimizing the energy losses and renewable energy costs was proposed to compare the solutions found by the algorithms.

2. PROBLEM FORMULATION

2.1 Objective function

The optimization problem was defined as the minimization of energy losses for the different hours of a day and the total annual cost related to the renewable energies used in the distribution network, as shown in (1).

$$OF = Min\left(w_1 * E_{Losses-a} + w_2 * TC_a\right) \quad (1)$$

Where w_1 and w_2 are constants used to find a solution from the possible combination of the energy loss and cost minimization, $E_{Losses-a}$ is the total annual energy losses of the distribution network, and TC_a is the total annual cost of renewable energy investment, maintenance, and operation.

2.2 Power losses

Power losses affect distribution networks due to the reduction of energy efficiency represented by the resistance and the reactance of lines and transformers. Power losses in a distribution network can be calculated as shown in (2) [17].

$$P_{Losses}=\sum_{i=1}^{n}\sum_{j=1}^{n} A_{ij}(P_iP_j + Q_iQ_j) + B_{ij}(Q_iP_j + P_iQ_j) \quad (2)$$

Where 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. Parameters A_{ij} and B_{ij} are defined in (3) and (4).

$$A_{ij}=\frac{R_{ij}\cos(\delta_i-\delta_j)}{V_iV_j} \tag{3}$$

$$B_{ij}=\frac{R_{ij}\sin(\delta_i-\delta_j)}{V_iV_j} \tag{4}$$

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

2.3 Annual energy losses

The total annual energy losses are calculated as the product of the sum of power losses during the day and the number of days in a year, as shown in (5) [6].

$$E_{Losses-a}=\sum_{h=1}^{24h}\left(P_{Losses-h}\right)*365 \tag{5}$$

Where $E_{Losses-a}$ is the annual energy losses, $P_{Losses-h}$ is the power loss each hour, and h is the hour. $E_{Losses-a}$ is used in the objective function to improve the energy efficiency of the network using the RDG.

2.4 Total annual cost

The total annual cost is calculated as the sum of the individual costs as defined in (6) [18].

$$TC_a=\sum_{i=1}^{n}MC_i+OC_i+IC_i \tag{6}$$

Where TC_a is the total annual cost, MC is the annual maintenance cost, OC is the annual operating cost, IC is the annual investment cost, and n is the number of renewable generators. The annual maintenance and operation cost of solar energy was assumed to be 21 $/kW-year, and the total annual maintenance and operation cost of solar energy was assumed to be 28 $/kW-year [19], [20]. The renewable energy investment cost IC was obtained using (7) [18].

$$IC=I*(1+int)^{pe}\left[\frac{int}{(1+int)^{pe}-1}\right] \tag{7}$$

Where I is the investment in solar photovoltaic panels or wind turbines to generate electricity, int is the interest rate, and pe is the planning study period, assumed to be 10 years.

2.5 Constraints

The objective function is subject to the real power balance, as shown in (8). This equation considers the main power source, the installed RDG, the total power load, and the total power losses.

$$P_{Slack}+\sum_{i=1}^{n}P_{RDGi}=\sum_{i=1}^{n}P_{Di}+P_{Losses} \tag{8}$$

Where P_{Slack} is the real power supplied by the slack bus, P_{RDGi} is the real power supplied by the RDG, P_{Di} is the real power demand of node i, and P_{Losses} is the total real power losses of the network.

Similar to the real power balance, the objective function is subject to the reactive power balance, as shown in (9). This equation considers the reactive power generation of the slack node, the reactive power of the installed RDG, the total power load, and the total power losses.

$$Q_{Slack}+\sum_{i=1}^{n}Q_{RDGi}=\sum_{i=1}^{n}Q_{Di}+Q_{Losses} \tag{9}$$

Where Q_{Slack} is the reactive power of the slack bus, Q_{RDGi} is the reactive power of the RDG located at bus i, Q_{Di} is the reactive power of the load located at bus i, and

Q_{Losses} is the reactive power losses of the network.

The voltage magnitudes at each node must be maintained between the maximum and minimum limits for all the solutions selected with each algorithm, as expressed in (10).

$$|V_i|^{min} \leq |V_i| \leq |V_i|^{max} \tag{10}$$

Where $|V_i|$ is the voltage magnitude of node i, $|V_i|^{min}$ is the minimum voltage magnitude of node i, and $|V_i|^{max}$ is the maximum voltage magnitude of node i. The solutions found for all the RDGs must comply with the maximum and minimum real and reactive power, as shown in (11) and (12).

$$P_{RDGi}^{min} \leq P_{RDGi} \leq P_{RDGi}^{max} \tag{11}$$

$$Q_{RDGi}^{min} \leq Q_{RDGi} \leq Q_{RDGi}^{max} \tag{12}$$

Where P_{RDGi} is the real power of RDG, P_{RDGi}^{min} is the minimum real power of RDG supplied to the node i, and P_{RDGi}^{max} is the maximum real power of RDG supplied to the node i. Q_{RDGi} is the reactive power of RDG supplied to the node i, Q_{RDGi}^{min} is the minimum reactive power of RDG supplied to the node i, and Q_{RDGi}^{max} is the maximum reactive power of RDG supplied to the node i.

Current constraints were also defined for the lines of the networks, considering the maximum current circulating through the branches, as shown in (13) and (14).

$$i_{ij} \leq i_{ij}^{max} \tag{13}$$

$$i_{ji} \leq i_{ji}^{max} \tag{14}$$

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

2.6 Load data

The load was modeled according to a typical consumption curve of distribution systems, as shown in Fig. 1. This curve is presented in per-unit values in order to multiply this factor by each load of the distribution network and represent similar variation during the day.

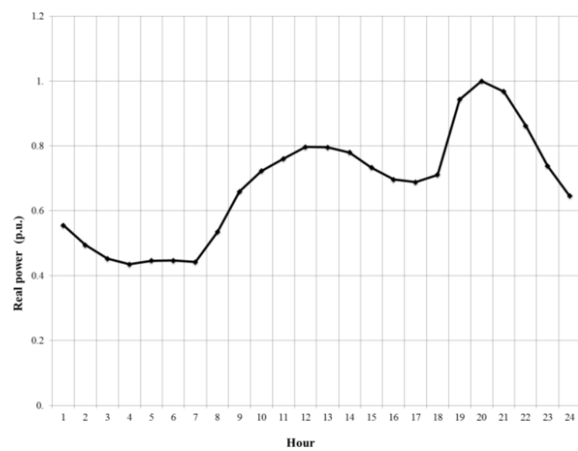

Fig. 1. Power load during a day. Source: Authors

This variation of load allowed the evaluation of the results of the location and size of RDG for the reduction of losses during a day. The loads were modeled as constant power for the different hours of the day.

2.7 Wind energy data

The wind generator transforms mechanical energy into electrical energy, considering the wind resources as input. In this research, the input variables of the wind generator were modeled using the wind speed resources shown in Fig. 2 [21].

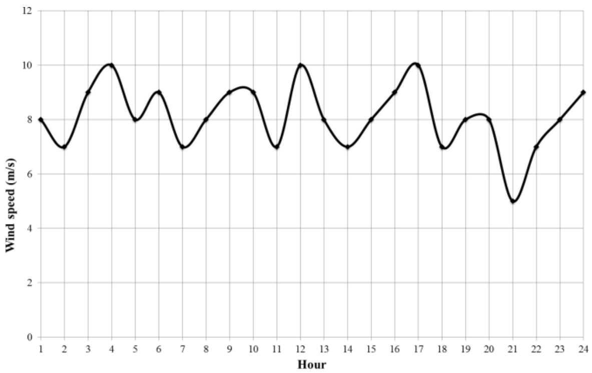

Fig. 2. Wind resources curve for a day. Source: Authors

A typical variation of real power generation supplied from wind turbines using the energy resources available was obtained using this curve of energy resources. The real and reactive power obtained from wind turbines were modeled as constant power for the power flow with the variation of production according to the available energy resources of the day.

2.8 Solar energy data

Fig. 3 shows the solar resources according to the number of hours in a day. These resources are used to obtain the real power from the PV panels. This solar radiation information has been obtained from local solar radiation measurements [22].

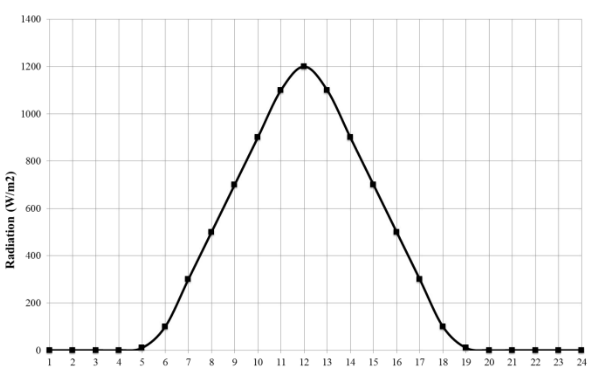

Fig. 3. Solar radiation curve for a day. Source: Authors

A typical variation of real power generation with the photovoltaic solar panels during the day can be represented using this solar radiation curve. The real power obtained from solar photovoltaic panels was modeled as constant power for the power flow according to the production of a typical panel with the available energy resources.

3. ALGORITHMS

Metaheuristic algorithms have obtained excellent results in mathematics, engineering, and other areas [23]. Intensification and diversification are two important aspects in the design of metaheuristics. Diversification refers to the ability to search in different regions of the search space, while intensification refers to the ability to find good quality solutions. A good search algorithm must have a balance between these two goals [24]. Fig. 4 shows the codification proposed in this work, to find solutions for the location and size of RDG.

x_1	y_1	z_1	x_2	y_2	z_2	…	x_i	y_i	z_i	…	x_n	y_n	z_n

Fig. 4. Problem codification for location and size of RDG. Source: Authors

Where z_i is the number of the bus where the renewable generator is located, $i = \{1,2,\ldots,n\}$. n is the number of elements to locate, x_i is the number of photovoltaic panels, and y_i is the number of wind turbines.

3.1 Cuckoo search

This optimization algorithm is based on the main instinctive behavior of the cuckoo bird [25]. This is a kind of parasitic bird dedicated to laying her eggs in the nests of other birds. Their chicks are then adopted and raised by these other species, providing a way of hiding some anomalies. If the bird eggs are discovered, they will be eliminated. Cuckoo birds have adopted ways of imitating the eggs of other birds to sneak into their habitat, as it is important that they not be discovered [26]. The optimization algorithm uses the following steps [25]:

1) Generate the initial population of n host nests x_i (i = 1, 2, …, n)
2) while (t < stop criterion)
   a) Obtain a cuckoo randomly and get its location using Lévy flights
   b) Evaluate the fitness F_i at the located point
   c) A random nest is selected among n (say j), and the evaluation of the fitness F_j is performed
   d) If $F_i > F_j$
   i) Replace j by the new solution F_j
   e) End if
   f) Abandon a fraction (p_a) of worse nests
   g) Keep the best solution
   h) Rank the solutions and find the current best
3) end while

The code simulates the behavior of this species, where each egg represents a new solution. A nest could have several cuckoo eggs, representing a set of new solutions. The bulk of the work is performed by the Lévy flight, which determines the distance to a nest, according to (15).

$$X_{t+1} = X_t + sE_t \quad (15)$$

Where X_{t+1} is the new position, X_t is the actual position, and E_t is obtained from a normal distribution with zero mean and a standard deviation of 1 for random searches of n nests.

3.2 Bat-inspired algorithm

This algorithm is based on the behavior of bats and their special technique called echolocation [27]. These echoes are used by bats to identify and locate objects and to avoid obstacles when flying. They help bats identify their prey and find the right places to sleep. During echolocation, bats emit a series of high-frequency sounds, which makes the echo bounce off surrounding objects. This helps the bats determine the objects' size, form, and position so they can move accordingly [27]. The algorithm was proposed in [28], and the steps are as follows:

1) Generate the initial population of bats
2) Generate the velocities of bats using (4)
3) Start with the frequency f_i, the pulse rate r_i, and the loudness A_i
4) Find the fitness for each bat i
5) Use the fitness vector to rank all the solutions as F_{best}
6) While $iter < iter_{max}$
   a) Find new solutions of x_{new} using the frequency and the velocities
   b) If $rand > r_i$
      i) Create a new solution close to the best
   c) End if
   d) Use random flights of bats to create new solutions
   e) Find the new fitness $F_{new}(x_{new})$
   f) If ($F_{new} < F_{best}$ and $rand < A_i$)
      i) 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}
7) End while

The frequency f_i can be calculated using (16), and the velocity is updated using (17) [27].

$$f_i = f_{\min} + (f_{\max} - f_{\min}) * b \quad (16)$$

$$v_i^k = v_i^{k-1} + (x_i^k - x_{best}) f_i \quad (17)$$

Where f_{max} is the maximum frequency, f_{min} is the minimum frequency, and β is a normally distributed 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. A new position of the particle x_i^k is calculated with the new velocity v_i^k and the previous position x_i^{k-1}, as shown in (18).

$$x_i^k = x_i^{k-1} + v_i^k \quad (18)$$

3.3 Harmony search

Harmony search is based on a population that mimics the natural behavior of musicians when cooperating using their instruments to achieve a fantastic harmony by aesthetic standards. This algorithm explores the search space of a set of data contained in the parallel optimization environment, where every harmony vector is generated intelligently by the exploration and exploitation of a search space. This algorithm was first proposed by Zong Woo Geem in 2001 [29] and the steps used in this research paper are described as follows:

1) Define the parameters of the algorithm
2) Define the initial population of the vector *HM*
3) Rank and select the best solutions and evaluate the fitness F_{best}
4) While $iter < iter_{max}$:
    a) Generate new solution x_{new}
    b) Calculate the new fitness
    c) Update the vector *HM*
    d) Update the best harmony vector
    e) Rank and select the best solution and the fitness F_{best}
5) End while

The steps presented in this work were programmed and adjusted to solve the location of RDG in distribution networks.

4. RADIAL DISTRIBUTION NETWORK

The 33-node radial distribution network was used to test the algorithms for the energy losses and cost minimization [30]-[32]. The specifications of the distribution network are presented in Table 1.

The 33-node radial distribution network has 33 nodes with 1 feeder and 32 possible nodes to locate RDG. Fig. 5 shows the diagram of the 33-node radial distribution network [30], [31]. The load considered was 3715 kW and 2300 kVAr, and the power generated was considered to be 3926 kW and 2443 kVAr. The minimum and maximum voltage magnitudes for all nodes were defined as $|V_i|^{min} = 0.9$ p.u. and $|V_i|^{max} = 1.1$ p.u., respectively.

Table 1. Specifications of the Radial Distribution Network. Source: Authors

Elements	33-node test feeder
Nodes	33
Lines	32
Feeder node	1
Transformers	0
Loads	32

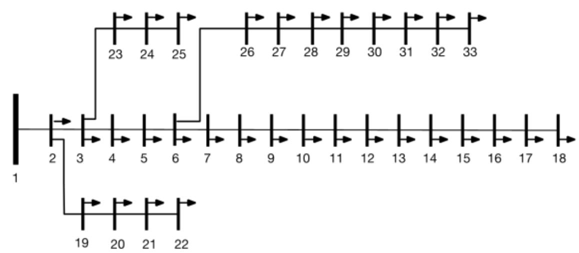

Fig. 5. 33-node radial distribution network. Source: Authors based on [30]

This radial distribution network was used to test the CS, BA, and HS when installing solar panels and wind generators. The results obtained by the algorithms were compared considering single renewable generators as well as combinations of generators.

5. SIMULATIONS

To determine the best location of RDG, the annual energy losses and the annual renewable energy costs were evaluated for each solution. Multiobjective algorithms were tested using 28 cases, changing renewable generators and the weights of the objective functions. Each case study considered the location and size of 5 generators with the possibility of locating solar photovoltaic panels and wind turbines for the distribution network. The parameters of the search were established as 200 particles and 500 iterations.

6. RESULTS AND DISCUSSION

Fig. 6 shows the results of the algorithms for the minimum fitness solution used in this research. This figure represents the behavior of the algorithms to reduce the fitness, given a weight defined as $w_1 = 1$ and $w_2 = 0.1$.

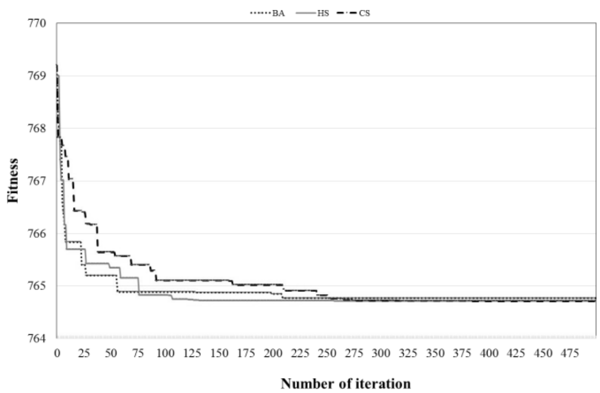

Fig. 6. Fitness reduction in the 33-node radial distribution network. Source: Authors

In Fig. 6, it is observed that algorithms begin reducing the objective functions with different speeds, but all finally find the best solution. Although CS is slower than the other algorithms, the best solution is found around 250 iterations. The BA quickly finds good solutions, but that algorithm sometimes becomes trapped in a local optimum. HS continually reduces the fitness, finding the best results after running more iterations. Fig. 7 shows the results of the multiobjective algorithms for location and size of solar photovoltaic panels.

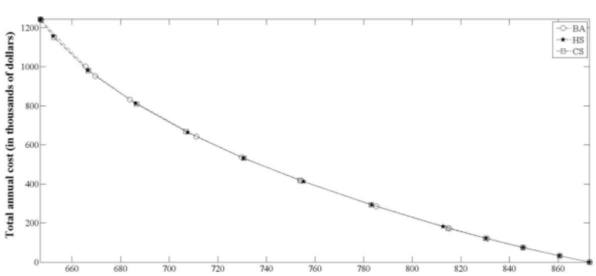

Fig. 7. Results of inclusion of solar generation for the 33-node radial distribution network. Source: Authors

This figure shows the evaluation of the different weights on the Pareto front. The simple Pareto front can be interpreted as the maximum values for the combination of energy loss reduction and the cost of renewable energies invested in the distribution network. As the investment in renewable energies increases, the energy losses in the distribution network are reduced. The algorithms arrive at similar results in the search for the best solutions, forming the line of a Pareto front.

The three algorithms find good results with points close to the other solutions, especially for weights that represent the lowest cost of renewable energies. When costs are high and power losses are low, the figure shows that the performance of the algorithms is not similar. The CS has the best performance for high costs, while the BA has the worst performance. However, the results obtained with the algorithms when the costs are low are very similar. Fig. 8 shows the results of the algorithms for location and size of wind turbines in the distribution network. This figure shows the different points evaluated to form a simple Pareto front.

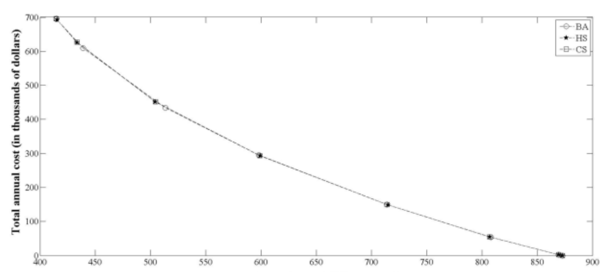

Fig. 8. Results of inclusion of wind generation for the 33-node distribution network. Source: Authors

Like the solutions with photovoltaic panels, the location of wind generators gives similar solutions with all algorithms. For cases with a low number of generators and investment, or cases of low reduction of energy losses, the three algorithms have similar behavior, finding similar results.

For cases with a large number of wind turbines, the solutions differ and are more notable for the solutions obtained with the BA. Table 2 shows the fitness found with the different algorithms after minimizing the annual energy losses and annual renewable energy costs, according to (1).

This table shows the results for different combinations of w_1 and w_2, according to the renewable sources tested in the problem. Results show that the three algorithms perform well for the problem tested with the multiobjective function. Table 2 shows that despite the small differences between the solutions found with the algorithms, CS obtained the best results for 64% of the cases studied. As the results obtained with the different algorithms are similar, the three algorithms have good behavior to solve the problem.

7. CONCLUSIONS

This paper presented an evaluation of the performance of the BA, HS, and CS algorithms to locate renewable energies in distribution networks with multiobjective functions, defined as minimizing the annual energy losses and annual renewable energy costs. Different points in the Pareto front were evaluated to identify the performance of the algorithms in search of the best solutions. The three algorithms found points close to the Pareto front, confirming the good performance of all algorithms to solve the problem. The BA had more issues in the search for the best solutions for a large number of generators to locate than the other algorithms, and the HS and CS had better performance, although the best solutions were found with the CS.

Table 2. Minimum fitness found with metaheuristic algorithms. Source: Authors.

Scenario	Alg	Solar Photovoltaic Panels				Wind turbines			
		w_1	w_2	Fitness	Pos	w_1	w_2	Fitness	Pos
1	BA	1	0.01	659.50	2	1	0.10	484.41	2
	HS	1	0.01	659.43	3	1	0.10	484.57	3
	CS	1	0.01	659.32	1	1	0.10	484.21	1
2	BA	1	0.10	764.72	1	1	0.30	627.78	3
	HS	1	0.10	764.92	3	1	0.30	627.61	2
	CS	1	0.10	764.72	2	1	0.30	627.57	1
3	BA	1	0.16	813.95	3	1	0.50	730.69	3
	HS	1	0.16	813.87	1	1	0.50	730.20	2
	CS	1	0.16	813.89	2	1	0.50	730.19	1
4	BA	1	0.22	846.03	3	1	0.70	804.67	3
	HS	1	0.22	845.89	1	1	0.70	804.36	2
	CS	1	0.22	845.91	2	1	0.70	804.36	1
5	BA	1	0.28	863.57	3	1	0.90	848.97	3
	HS	1	0.28	863.55	1	1	0.90	848.59	1
	CS	1	0.28	863.56	2	1	0.90	848.61	2
6	BA	1	0.34	870.93	3	1	1.10	867.28	3
	HS	1	0.34	870.93	2	1	1.10	867.25	2
	CS	1	0.34	870.93	1	1	1.10	867.25	1
7	BA	1	0.40	872.90	1	1	1.30	872.89	1
	HS	1	0.40	872.90	1	1	1.30	872.89	1
	CS	1	0.40	872.90	1	1	1.30	872.89	1

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