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Research Article

A Hybrid Evolutionary Approach to Design Off-Grid Electrification Projects with Distributed Generation

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A hybrid evolutionary approach is proposed to design off-grid electrification projects that require distributed generation (DG). The design of this type of systems can be considered as an NP-Hard combinatorial optimization problem; therefore, due to its complexity, the approach tackles the problem from two fronts: optimal network configuration and optimal placement of DG. The hybrid scheme is based on a particle swarm optimization technique (PSO) and a genetic algorithm (GA) improved with a heuristic mutation operator. The GA-PSO scheme permits finding the optimal network topology, the optimal number, and capacity of the generation units, as well as their best location. Furthermore, the algorithm must design the system under power quality requirements, network radiality, and geographical constraints. The approach uses GPS coordinates as input data and develops a network topology from scratch, driven by overall costs and power losses minimization. Finally, the proposed algorithm is described in detail and real applications are discussed, from which satisfactory results were obtained.

1. Introduction

The increasing penetration of distributed generation and renewable energy sources (RES) have brought new opportunities to improve electrical systems. For instance, *optimal placement* and adequate *size estimation* of DGs, with a suitable *network configuration*, can improve an electrical system by reducing power losses, excessive generation, and overall costs. These goals can potentially improve the service quality, reliability, and voltage profiles provided to end customers and enable the integration of RES to the grid [1–4].

Since distribution networks (DNs) display high complexity in terms of their topology, their optimal planning is not an easy task. For the design, the optimal number, placement, and size of generation plants must be considered, in order to feed all users under strict power quality requirements. Furthermore, the system must be designed to minimize power losses and investment costs. This problem becomes even more challenging when DG is involved. Additional difficulties include the consideration of nonuniform loads, the future projection of user growth, the remote location of RES, and geographical constraints.

The optimal planning of DNs with DGs has motivated several contributions that can be gathered in two main groups:

(1) Optimal Placement and/or Sizing of DGs (see, e.g., [5, 6]). Under this approach, a DN is improved by selecting the optimal size and placement of DGs, for a given network topology. Here the objective function can be simple or multiobjective, focusing on the minimization of costs and power losses [7]. For example in [8], an improved nondominated sorting genetic algorithm (INSGA) is proposed for optimal placement and sizing of DGs considering line losses, voltage deviation, and stability. In [9], a linear programming approach based on a mixed-integer program is presented to reduce investment costs via optimal placement and sizing of DGs.

(2) Optimal Reconfiguration of Distribution Networks with Distributed Generators (see, e.g., [10]). This method is based on the opening/closure of predefined switches to partially change the topology and structure of DNs (see [11–17]). The main objective of these contributions is to find a new network topology, which alleviates power quality issues and minimizes power losses as well as investment costs. Although

these optimization methods offer satisfactory results, the location of DGs has to be preestablished.

Even though a simultaneous solution of the two research directions outlined above is highly desirable, we can find only a few contributions with this aim, e.g., [18–20]. Particularly in [18], a metaheuristic method based on a greedy randomized adaptive search procedure (GRASP) is used to design off-grid electrification systems with distributed generation. However, a nontrivial computational effort is demanded as the complexity of the system increases. In [19], a genetic algorithm-based tool is tested to solve a dynamic multistage planning that aims at sizing and locating substations in distribution networks. This algorithm generates satisfactory results, as long as a set of plausible substation locations and branch interconnections are provided *a priori*. In [20], a model for active distribution systems expansion planning based on genetic algorithms is presented, where DG integration is considered together with network reconfiguration. The possible drawback of this model is that only considers the minimization of a single objective function based on costs and cannot guarantee the network radiality and accomplishment of power quality parameters.

Unlike grid-connected systems, small isolated projects have more freedom to locate DGs in different points of the network, even small generation units can be installed at each house. This implies a greater number of possible configurations, becoming a hard combinatorial optimization problem. The main question about these types of systems is how many DGs we should install to feed all users, satisfying power quality constraints and minimizing costs. For example, if a fully centralized system (only one DG for all users) is chosen, the total investment cost will decrease, but the power losses and quality issues may increase as well. On the other hand, if a fully decentralized system (a DG per user) is chosen, the total power losses will be reduced but the investment cost may increase. We illustrate these scenarios in Figure 1(a).

Considering the aforementioned problem and the lack of investigation related to this type of optimization problems, a *hybrid GA-PSO* approach is proposed to design off-grid electrification projects, which require multiple placement of DGs. The GA-PSO scheme is based on optimal network reconfiguration and optimal placement of DGs. Finally, to prove the effectiveness of the proposed algorithm several experiments have been made on two real cases where distributed photovoltaic generation (DPG) has to be installed.

This paper is organized as follows. Section 2 formulates the problem and its objective functions. Section 3 describes the GA-PSO optimization approach. Section 4 provides numerical results, and Section 5 summarizes the main contribution and conclusions of this paper.

2. Problem Formulation

2.1. Objective Functions. Based on the model of Figure 1(a), the optimization approach must find a system configuration c, to minimize power losses (f_a) and investment costs (f_b) with respect to an installed capacity. These two objectives are selected because this type of electrification projects usually is implemented at low voltage levels, where a high R/X ratio causes more power losses and quality issues, affecting the efficiency of the system. Furthermore to minimize these issues, the network infrastructure can be improved and the number of DGs is increased. This implies higher investment costs that must also be reduced; therefore the multiobjective problem can be formulated as

$$\min\left[f_a(c),\ f_b(c)\right]; \quad c \in \Upsilon \tag{1}$$

where Υ is the space of feasible solutions.

The first objective f_a can be expressed as

$$f_a(c) = \sum_{n=1}^{\eta} g_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \tag{2}$$

where η is the total number of branches in the network, (i, j) are the two nodes of the branch, and g_{ij} is the conductance between the respective nodes. (V_i, V_j) are the voltage magnitudes at each node, and θ_{ij} is the difference between nodal phase angles θ_i and θ_j (see Sec. 6.8 and 9.1 of [21]). Considering DPG, the second objective f_b can be formulated as

$$f_b(c) = \sum_{n=1}^{\lambda} \mathscr{I}_n \iota_n + \sum_{n=1}^{\varsigma} \mathscr{B}_n \nu_n + \sum_{n=1}^{\psi} l_n \varrho_n + \tau\vartheta \tag{3}$$

where λ is the total number of inverter types, $\mathscr{I}_n$ is the number of inverters for each type, and ι_n is its cost. ς is the total number of battery types, $\mathscr{B}_n$ is the number of batteries for each type, and ν_n is its cost. ψ is the total number of conductor types, l_n is their total length, and ϱ_n is the cost per meter of each n type conductor. Finally, τ is the total number of photovoltaic panels and ϑ is the cost of each one.

2.2. Constraints. The optimization model is subject to the following constraints.

2.2.1. Equality Constraints. Power-flow equations is expressed as

$$\begin{aligned} P_{DG_i} - P_{ld_i} &= V_i \sum_{j=1}^{N_b} V_j \left(Y_{g_{ij}}\cos\theta_{ij} + Y_{b_{ij}}\sin\theta_{ij}\right) \\ Q_{DG_i} - Q_{ld_i} &= V_i \sum_{j=1}^{N_b} V_j \left(Y_{g_{ij}}\sin\theta_{ij} + Y_{b_{ij}}\cos\theta_{ij}\right) \end{aligned} \tag{4}$$

where (P_{DG_i}, Q_{DG_i}) are the active and reactive generation outputs, and (P_{ld_i}, Q_{ld_i}) are the active and reactive loads at node i. $Y_{g_{ij}}$ and $Y_{b_{ij}}$ are the conductance and susceptance of the admittance matrix, respectively; and N_b is the number of buses.

2.2.2. Inequality Constraints. Load bus voltage constraints are

$$V^{min} \le V_i \le V^{max}, \tag{5}$$

generation limits are

$$S_{DG}^{min} \le S_{DG_i} \le S_{DG}^{max}, \tag{6}$$

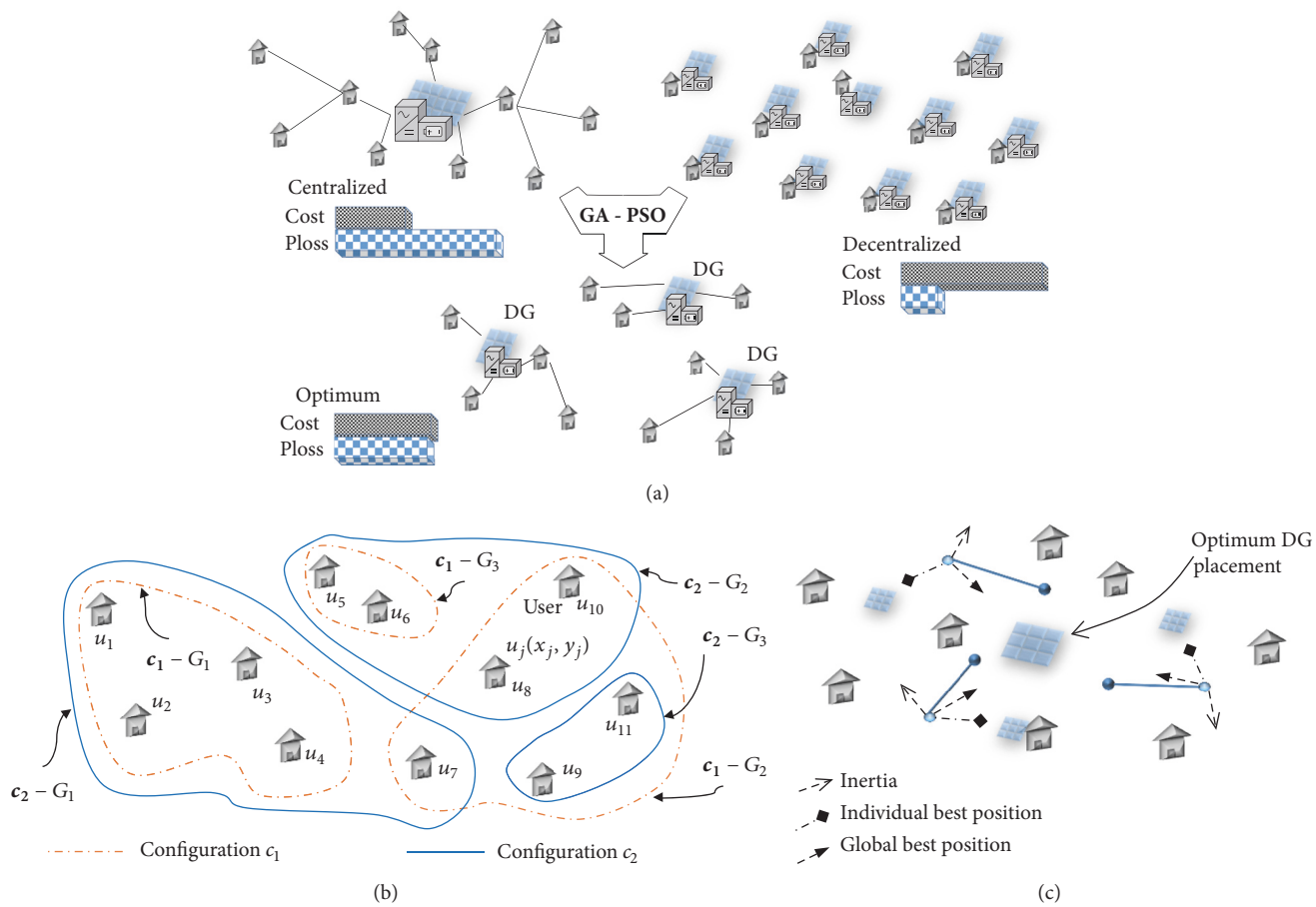

Figure 1: GA-PSO approach. (a) Problem definition. (b) Optimal network configuration by the GA. (c) Optimal placement of DGs by the PSO.

energy storage (battery) constraints are

$$SB_{DG}^{min} \leq SB_{DG_i} \leq SB_{DG}^{max}, \tag{7}$$

thermal limits are

$$I_{ij} = \left|\left(\overline{V}_i - \overline{V}_j\right) \cdot y_{ij}\right| \leq I^{max}, \tag{8}$$

and geographical constraints are

$$\forall br_{ij}^{rst} \in \Gamma \neq br_{ij}, \tag{9}$$

where $(S_{DG}^{min}, S_{DG}^{max})$ are the apparent power limits for DGs, and $(SB_{DG}^{min}, SB_{DG}^{max})$ are the permissible limits to store energy in batteries. I^{max} is the maximum electric current for a conductor, and y_{ij} is the admittance of a branch br_{ij}. Finally, Γ is the set of restricted branches (br_{ij}^{rst}), which are unable to be used in the network.

2.3. Treatment of Constraints. Considering that there are only two objective functions, scalarization [22] was chosen to solve this constrained multiobjective optimization problem in order to reduce the computational effort. Assigning a numerical quality function to objectives (2) and (3), we can combine these scores into a single fitness score, and the inequality constraints (5)-(8) can be satisfied through penalizing the same fitness score. The equality constraints (4) can be satisfied during the power-flow calculation and (9) during the network construction, so the constrained optimization problem can be transformed into the unconstrained form expressed as follows:

$$\begin{aligned}
&\min f(c) \\
&\quad = w_1 \cdot f_a(c) + w_2 \cdot f_b(c) \\
&\qquad + w_3 \sum_{i=1}^{Nb} \left|\min\left(V_i - V^{min}, 0, V^{max} - V_i\right)\right| \\
&\qquad + w_4 \sum_{n=1}^{\eta} \max\left(I_{ij} - I^{max}, 0\right) \\
&\qquad + w_5 \sum_{i=1}^{\kappa} \left|\min\left(S_{DG_i} - S_{DG}^{min}, 0, S_{DG}^{max} - S_{DG_i}\right)\right| \\
&\qquad + w_6 \sum_{i=1}^{\kappa} \left|\min\left(SB_{DG_i} - SB_{DG}^{min}, 0, SB_{DG}^{max} - SB_{DG_i}\right)\right|
\end{aligned} \tag{10}$$

where κ is the total number of DGs or groups; w_1 and w_2 are constant weights to balance the objective functions; and w_3, w_4, w_5, and w_6 are penalty values.

3. GA-PSO Optimization Approach

The optimal planning of small off-grid electrification projects, which require distribution generation, can be classified as a nonconvex, nonlinear, and mixed-integer optimization problem. Given its complexity, the problem is faced from two fronts:

(i) Optimal network configuration: a GA is used to find the best network configuration and the optimal number of DGs, where overall costs and power losses are minimized; see Figure 1(b). Due to the special characteristics of a distribution network, a heuristic mutation operator is proposed to improve the searching capability.

(ii) Optimal placement of distributed generation: a PSO is used to find the optimal placement of DGs, minimizing power losses and quality issues; see Figure 1(c). For this process, a greedy algorithm is implemented to construct the network and maintain its radiality.

The operation of each stage is described as follows.

3.1. Optimal Network Configuration by the GA

3.1.1. GA Overview. The GA is a metaheuristic optimization method inspired by natural evolution [22]. It is based on a population that evolves with the aid of four genetic operators.

(a) Representation. Each possible configuration/solution must be represented as a string (chromosome), containing the relevant information to be evaluated. In our case, an integer vector representation is used. *(b) Selection.* This operator creates a new generation by selecting the best individuals from an older population. In our case, a *stochastic universal sampling method* (SUS) is used [22]. *(c) Recombination.* This operator swaps chromosome segments (genes) between two individuals to create an offspring. In our case an *n-point crossover* method is used. *(d) Mutation.* The basic mutation operator causes random changes on the alleles (p_{ij}) of few chromosomes, in order to improve the diversity of the gene pool. In our case, a heuristic based method (*intelligent mutation*) is implemented.

3.1.2. Initialization and System Representation. The algorithm starts by creating an initial random population, on which each individual is a possible configuration of the system. These configurations are represented as integer vectors, i.e.,

$$c_i = \left[p_{i1} \quad p_{i2} \quad p_{i3} \quad \cdots \quad p_{i\mu}\right]; \quad p_{ij} \in \mathbb{Z}^+ \; i = 1, 2 \ldots m \tag{11}$$

where m is the size of the population and μ is the total number of users. Each *user* (u_j) can belong to any group (G_n) within a *configuration/chromosome*, as shown in Figure 1(b). Hence the entire population can be represented by a matrix whose p_{ij} values represent the group number of the *j-th* user in the *i-th* chromosome, i.e.,

$$\text{Population} = \begin{array}{c} \\ c_1 \\ c_2 \\ \vdots \\ c_m \end{array} \begin{array}{c} \begin{array}{ccccc} u_1 & u_2 & u_3 & \cdots & u_\mu \end{array} \\ \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1\mu} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2\mu} \\ & & \vdots & & \\ p_{m1} & p_{m2} & p_{m3} & \cdots & p_{m\mu} \end{bmatrix} \end{array}. \tag{12}$$

For example, the configuration c_2 of the Figure 1(b) can be represented by

$$c_2 = \begin{array}{c} \begin{array}{ccccccccccc} u_1 & u_2 & u_3 & u_4 & u_5 & u_6 & u_7 & u_8 & u_9 & u_{10} & u_{11} \end{array} \\ \begin{bmatrix} 1 & 1 & 1 & 1 & 2 & 2 & 1 & 2 & 3 & 2 & 3 \end{bmatrix}. \end{array} \tag{13}$$

We should note that each user depends on GPS coordinates, i.e., $u_j(x_j, y_j)$, and the entire set of users are sorted with respect to the x-coordinate.

3.1.3. Fitness Evaluation. The GA performs the evaluation of each chromosome through a suboptimization algorithm, i.e., the PSO. Each chromosome is composed of groups (G_n) which must be optimized by the PSO. In this process, each group is evaluated through (10), and these results are returned to the GA to calculate the chromosome fitness by the following:

$$f_i(c_i) = \sum_{n=1}^{\kappa} f_n(G_n); \quad G_n \in c_i; \; i = 1, 2, \ldots, m. \tag{14}$$

3.1.4. Selection. After the fitness evaluation, some individuals must be selected to form a mating pool. For this SUS was chosen since this method gives more opportunities for reproduction to those individuals with better fitness. To apply this method, a probability distribution vector must be found, based on the expected number of copies of each individual, i.e.,

$$ec_i = m \cdot \frac{f_i}{\sum_{i=1}^{m} f_i} \tag{15}$$

where $f_i / \sum_{i=1}^{m} f_i$ is the probability of each individual according to its fitness.

The outline of SUS is shown in Pseudocode 1.

3.1.5. Recombination. From the mating pool, two random individuals are selected to carry out the crossover and create an offspring. The chromosomes are broken into several segments of contiguous genes, and the offspring are created by taking alternative segments from the parents. For this operation n random crossover points in $[1, \mu - 1]$ must be chosen. In our case due to the extensive chromosome length, the number of crossover points is established by (16) where δ is a constant value between [0.01, 0.1].

$$n = \max\left[round\left(\mu \cdot \delta\right), 2\right] \tag{16}$$

For example, taking the chromosomes c_1 and c_2 of Figure 1(b), with crossover points at 4 and 8 the result is

$$\begin{matrix} c_1\,[1 & 1 & 1 & 1 & | & 3 & 3 & 2 & 2 & | & 2 & 2 & 2] \\ c_2\,[1 & 1 & 1 & 1 & | & 2 & 2 & 1 & 2 & | & 3 & 2 & 3] \end{matrix} \longrightarrow \begin{matrix} c_1'\,[1 & 1 & 1 & 1 & 2 & 2 & 1 & 2 & 2 & 2 & 2] \\ c_2'\,[1 & 1 & 1 & 1 & 3 & 3 & 2 & 2 & 3 & 2 & 3]. \end{matrix} \tag{17}$$

3.1.6. Mutation. After the recombination, some individuals from the population may suffer a mutation. Usually, the basic mutation operator performs random changes on the *alleles*(p_{ij}) of the chromosome, but, in our case, a heuristic method ($\mathscr{M}$) is implemented to perform specific changes. A configuration c_i mutates if a random value in [0,1] is superior to a mutation rate ϖ, i.e.,

$$c_i' = \begin{cases} \mathscr{M}(c_i), & \text{if rand } [0,1] \geq \varpi \\ c_i, & \text{if rand } [0,1] < \varpi. \end{cases} \tag{18}$$

This *intelligent mutation* selects the end-nodes of each group (e.g., see Figure 2(a)) and compares distances to other DGs. If a shorter distance is eventually found, the end-node permutes to such group.

The mutation rate is established by (19) to increase the use of $\mathscr{M}$ at the beginning of the search, for later reducing its use in the last iterations (t).

$$\varpi = 1 + \frac{\left(\varpi^{init} - 1\right)\left(t - t^{max}\right)}{\left(1 - t^{max}\right)}. \tag{19}$$

The selection, recombination, and mutation are repeated until an optimum is reached.

3.2. Optimal DG Placement by the PSO

3.2.1. PSO Overview. The PSO is a swarm intelligence technique inspired by social behavior of bird flocking or fish schooling [23], where each particle is a possible solution for the optimization problem. These particles depend on three factors: *individual best position, global best position,* and *inertia*; see Figure 1(c). At each iteration, their velocity and direction are adjusted until finding a global optimum. The equation that governs the movement of each particle is represented by

$$v_i^{(t+1)} = w_I v_i^{(t)} + w_C r_1 \left[\rho_i - \chi_i^{(t)}\right] + w_S r_2 \left[\sigma_n - \chi_i^{(t)}\right] \tag{20}$$

where $v_i^{(t)}$ and $\chi_i^{(t)}$ are the velocity and the actual position of each particle, ρ_i is the best position found by each particle, and σ_n is the best position found by the entire group. w_I, w_C, and w_S are weights of inertia, cognitive behavior, and social behavior, respectively. r_1 and r_2 are random values between [0,1], and t is the iteration number. Finally, the position of each particle is updated by

$$\chi_i^{(t+1)} = \chi_i^{(t)} + v_i^{(t+1)}. \tag{21}$$

In our case, each particle will be a possible location for a DG in a group G_n.

3.2.2. Initialization. The PSO assigns a number of χ_i particles to each group within a chromosome by means of

$$\psi = \max\left[round\left(\xi \cdot \gamma\right), 2\right] \tag{22}$$

where ξ is the length of each G_n set, and γ is a constant value between [0.1, 0.5]. Subsequently, the particles are located at random within the set, as shown in (23).

$$G_n = \left[u_1 \;\; \chi_1 \;\; u_3 \;\; \cdots \;\; \chi_2 \;\; \cdots \;\; \chi_\psi \;\; u_\xi\right]; \qquad n = 1, 2, \ldots \kappa. \tag{23}$$

Figure 2(b) shows a graphical representation of this process, where two particles (e.g. represented as photovoltaic panels) are located in each group.

3.2.3. Particle Evaluation. The fitness $f_i(\chi_i)$ of each particle is calculated through (10), performing the following steps.

(a) Network Construction. A radial distribution network can be found by considering it as a weighted undirected graph, from which we can obtain a minimum spanning tree by using a traditional *Prim's algorithm*. From a starting node, this algorithm adds at each step the shortest possible branch to make a new link to another node. An example of this process is shown in Figure 2(b), for the group G_1. The construction starts at the generation center χ_1, then the following nodes to add based on the *Euclidean distance* are u_3, u_4, u_7, and u_1 through the branches $\overrightarrow{u_2u_3}$, $\overrightarrow{u_2u_4}$, $\overrightarrow{u_4u_7}$, and $\overrightarrow{u_2u_1}$ (dotted red lines). To avoid selecting a restricted branch (e.g., $\overrightarrow{u_3u_1}$) a penalty is added to its distance; therefore another alternative must be taken. Applying this penalty the inequality constraint (9) is satisfied.

(b) Power-Flow Computation. Using the y_{ij} admittances of the branches found in the previous step, an admittance matrix (Y) can be calculated. Considering the location of each particle χ_i as the slack bus of the system, and the remaining nodes as PQ type, the power-flow equations (4) can be solved using an iterative method, such as Newton-Raphson or Gauss-Seidel. With these results, $f_a(\chi_i)$ can be calculated through (2).

(c) DG Sizing and Cost Calculation. Considering a DPG, the required capacity for a small photovoltaic system can be calculated by

$$CAP_{PV} = h^{0.9} \cdot E \cdot \frac{\varepsilon}{(30 \cdot \Lambda)} \tag{24}$$

where h is the number of users, E is the average energy consumption per month (kWh/month), ε is a compensation

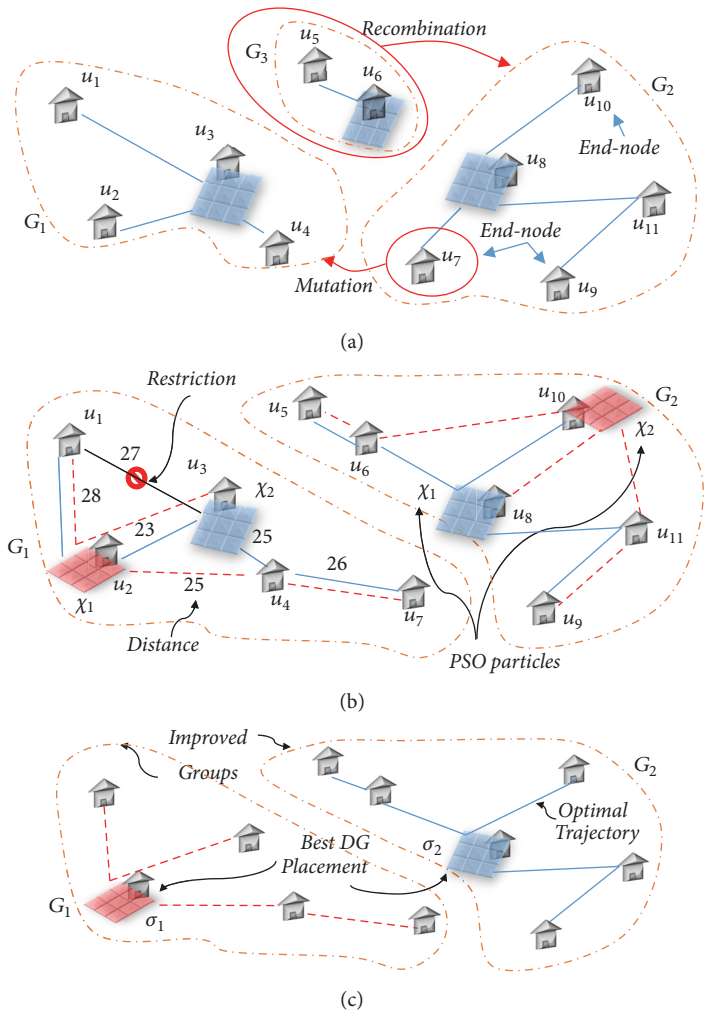

Figure 2: GA-PSO process. (a) GA operation. (b) PSO operation. (c) Configuration result.

```
i = 0; accum = 0;
WHILE individuals < m
j = rand[0, 1]; i = i + 1; accum = accum + ec_i;
    WHILE accum > j
        Select individual c_i; j = j + 1;
    END
END
```

Pseudocode 1: SUS pseudocode.

factor for power losses, and Λ is the average solar radiation. Furthermore, the size of the battery bank can be calculated by

$$CAP_{Batt} = CAP_{PV} \cdot RD \cdot \Lambda \cdot \frac{1000}{(V_{in} \cdot \epsilon)} \tag{25}$$

where RD is the number of reserve days, V_{in} is the input voltage for the inverter, and ϵ is the discharge rate. Finally, these results are compared with commercial equipment, and those that can supply the required demand will be chosen.

Once the equipment is established, $f_b(\chi_i)$ can be calculated through (3).

3.2.4. Saving Results and Updating Data. After the evaluation, if $f_i(\chi_i)$ is the lowest personal fitness found so far by the particle χ_i, its current position is saved in ρ_i. At the same time, if ρ_i is the best position among all the particles this result is saved in σ_n, and the fitness of the group is established by

$$f_n(G_n) = f(\sigma_n). \tag{26}$$

Using the memories ρ_i and σ_n, each particle updates its velocity and direction through (20) and (21). Finally, the DG for each group will be placed in σ_n, as shown in Figure 2(c).

3.3. Complete Algorithm of the GA-PSO Approach. The flowchart of the proposed algorithm is shown in Figure 3.

4. Experiments and Results

The hybrid GA-PSO optimization approach was applied to two rural communities in the Ecuadorian Andes where

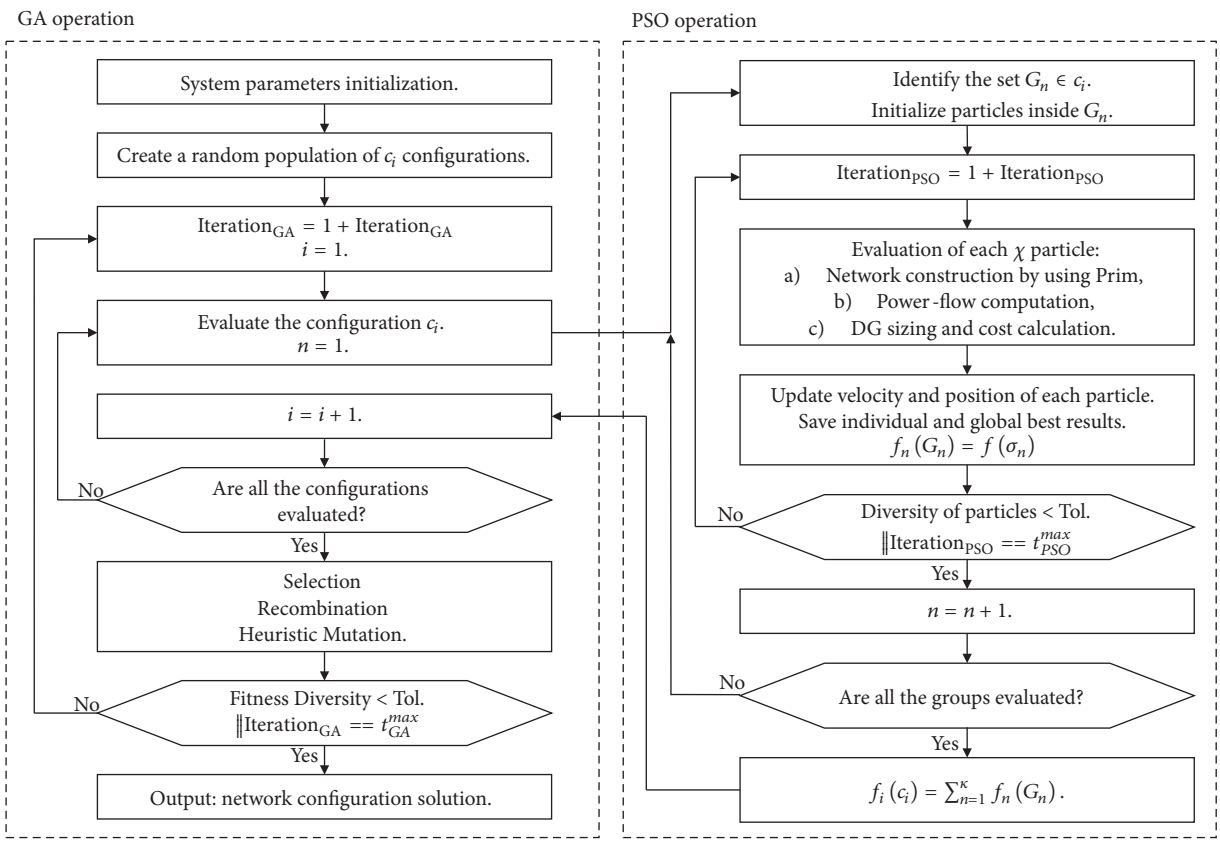

Figure 3: Flow chart of the GA-PSO algorithm.

an energization planning was needed. Each community is denoted as CM1 and CM2, hosting 36 and 48 users, respectively. Distributed photovoltaic generation was selected because the area of study is located at 2500 m above sea level, at 0° latitude, allowing an average solar radiation of 4.4 kWh/m^2, and an average temperature of 18°C. These data were obtained from RETScreen [24]. The geographical coordinates for each community were obtained in situ (see. Figures 4 and 5). Each GPS point can represent either a load, a cluster of loads, or a waypoint (usually used when a branch has a restriction). Due to the lack of an existing distribution system, battery banks were implemented. The entire system is designed at 240 V, with a voltage drop limit (ΔV) of 5.5%, a peak load per user of 2.23 kVA, and an average energy consumption of 200 kWh/month. The impedance of the different conductors was obtained from libraries available in ETAP™. The main characteristics and reference prices ($US) of the considered equipment are listed in Table 1. We must note that the considered inverters can control the power supply at a given voltage-frequency and charge/use the battery bank according to the amount of generation.

Finally, the effectiveness of the proposed GA-PSO algorithm is tested under two scenarios: (1) simulating a centralized and decentralized system by blocking the number of DGs to be installed and (2) using a single objective fitness function and standard variation operators (crossover and mutation).

4.1. GA-PSO Optimal Results. The evolution process, for the GA-PSO scheme applied to CM1, is shown in Figure 4. Each capture shows the best configuration found until the *nth-evolution* with their respective fitness, power losses, and total costs. For each G_n group the required photovoltaic capacity and the size of the battery bank are detailed. The description of each element used in the graphic is shown in Table 2.

As we can see in Figure 4 the algorithm starts *from scratch*, taking the GPS points from CM1 to propose, initially, random configurations. In the following generations, the GA algorithm learns and proposes better configurations due to the selection, crossover, and mutation. At the same time, the PSO searches the best location for the DGs and evaluates the proposed configurations. In the first evolutions, the results are naturally *primitive*, since the number of groups can vary drastically, the configurations present no logic, and some points of the network violate the imposed constraints. However, after several evolutions, the system develops a defined structure and its fitness decreases as well as power losses and costs. For CM1, after 39 evolutions, the main result is the electrification of the entire community, installing 4 DGs with a configuration where power losses and costs are minimized.

To reach acceptable results some parameters must be tuned. For example, the constant weights w_1 and w_2 are the most difficult to establish because the balance of the

Table 1: Prices and main characteristics of the equipment.

Equipment	Characteristics	Capacities	Price/U.
PV panels	V_p = 29.3 Vdc	240 W	\$ 250
	I_p = 8.19 Adc		
Batteries	48 V	24 Ah	\$ 310
	Disch. R. = 0.8	40 Ah	\$ 475
		60 Ah	\$ 645
		90 Ah	\$ 725
		120 Ah	\$ 925
Inverters	V_{in} = 340-500 Vdc	5.5 kW	\$ 1675
	V_{bat} = 348 Vdc	10 kW	\$ 2925
	V_{out} = 240 Vca	12.5 kW	\$ 3285
	Eff = 0.98 %	15 kW	\$ 3665
		20 kW	\$ 4215
Conductors	ACSR	2 AWG	0.65 \$/m
		1/0 AWG	0.72 \$/m
		2/0 AWG	0.85 \$/m
		3/0 AWG	1.05 \$/m

Table 2: Nomenclature.

∘	Waypoint	—	2 AWG conductor
▽	One Load	- - -	1/0 AWG conductor
◇	Load Group	-·-·-	2/0 AWG conductor
□	Distributed Generation	- - - -	3/0 AWG conductor

Table 3: GA-PSO results for CM1 and CM2.

	CM1	CM2
Users	36	48
Best Fitness	9593	13089
Total Power Loss [kW]	1.83	3.53
Total Cost [\$]	95232	130050
DG units	4	5
Installed Capacity [kW]	60	85
Bat. Bank [Ah]	330	420
Max ΔV per node [%]	5.3	5.4
Total Evolutions	39	54
Iteration Time [min]	3	9

system, between *efficiency* and *investment costs*, depends on these two values. In order to select these components, several simulations were carried out, concluding that f_a must have more weight than f_b. Moreover, it is important to calibrate the penalty values w_3, w_4, and w_5, for the proper delimitation of the search space and to prevent the selection of unfeasible solutions within the evolutionary process. Therefore, it was found that satisfactory results can be obtained with $w_1 = 1$, $w_2 = 0.1$, $w_3 = 300$, $w_4 = 1500$, and $w_{5,6} = 10000$. Other established parameters are as follows: GA population number $m = 70$; the max-iteration number $t_{GA}^{max} = 300$, $t_{PSO}^{max} = 100$; crossover factor $\delta = 0.07$; and initial mutation rate $\varpi^{init} = 0.6$.

Applying the aforementioned parameters, the most recurrent results for CM1 and CM2, after 100 simulations, are summarized in Table 3, and the network design for CM2 is shown in Figure 5(b). From these results, we can notice that for each community the algorithm found well-balanced configurations since DGs' capacities were better used. This is verified by observing that the algorithm grouped as many users as possible to a DG until reaching the maximum voltage drop limit (5.5%), see, e.g., Figure 5(b), nodes $G_4 - u_{12}$ and $G_5 - u_2$. In addition, we must note that the PSO located the DGs at nodes where power losses, voltage deviations, and quality issues may be reduced; e.g., see Figure 5(b), $G_1 - u_5$, $G_5 - u_5$. This is demonstrated in Table 4, where other DG locations (for G_5) are evaluated.

Finally, although the possible configurations can be millions, the GA-PSO algorithm could find satisfactory results analyzing only a few cases (e.g., 1400 for CM1), from which it took the best *genes* to create better designs. This is validated with the convergence curve shown in Figure 6.

4.2. Case Studies

4.2.1. GA-PSO versus Centralized/Decentralized Systems. In the first scenario, we want to prove the effectiveness of the GA-PSO algorithm to find a balanced design between costs and power losses. In order to do this, the number of DGs is increased and decreased by one (with respect to the GA-PSO result) to obtain a *centralized* and *decentralized* reference model. This was done by blocking the number of DGs that the algorithm can install. As we can see in Figure 5(a) and Table 5, with one less DG, the total cost of the system is reduced, but there are quality issues for some users; e.g., see

Table 4: Results for different DG placement in CM2-G_5.

Node	Power Loss [kW]	Max ΔV [%]	Quality Issues
u_3	1.14	7.7	1
u_4	0.84	6.8	2
u_5	0.98	5.4	0
u_7	1.99	12.9	2

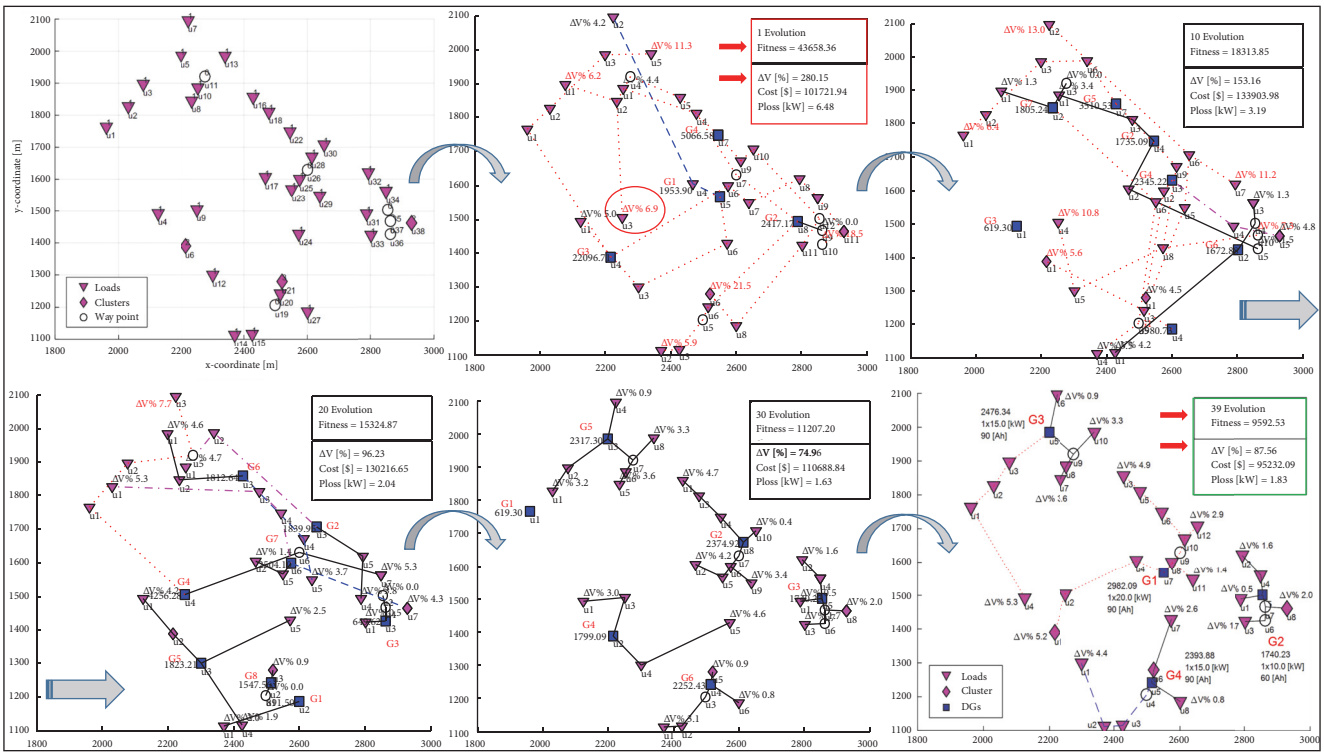

Figure 4: GA-PSO evolution process and result for CM1.

Figure 5(a) G_4, nodes u_6, u_{12}, u_{14}. On the other hand, with an extra DG, the total power loss is reduced but the total cost is increased, as shown in Figure 5(c). This demonstrates that the configurations found by the GA-PSO algorithm have the optimal number of DGs to minimize costs and satisfy the power quality constraints.

4.2.2. GA-PSO versus Single Objective/Standard Operators. In this scenario, the importance of a multiobjective fitness function and the need of improved variation operators are demonstrated. In order to do this, f_b is disabled to have a single objective fitness function and a 2-point crossover along with a common swap mutation operator [22] are used. The results are shown in Table 6, and as we can see, the single objective function has resulted in minor power losses and higher costs than the optimal model. The reason is that the algorithm evenly distributed the users between the DGs, wasting installed capacity in the process. Furthermore, without the counterbalance of f_b, the algorithm tends to install a DG per user; therefore, for the simulation, the number of DGs was preestablished in 4. On the other hand, the model with standard variation operators reports the worst results, being 20% more expensive and 25% more inefficient than the optimal model. This result is mainly due to the random changes of the users/loads from one group to another by the swap mutation operator. Therefore, we conclude that improved variation operators are extremely necessary to achieve satisfactory results in this type of optimization problems.

5. Conclusions

The proposed GA-PSO scheme is able to design off-grid electrification projects, which require multiple placement of distributed generation. The algorithm is based on optimal network configuration (via the GA) and optimal placement of DGs (via the PSO). The objective functions considered for this combinatorial optimization problem are the minimization of power losses and the minimization of investment costs. Due to the special characteristics of this type of electrification projects, a heuristic mutation method is proposed to improve the searching capability of the GA, and a greedy algorithm is implemented to construct a radial distribution network using GPS coordinates.

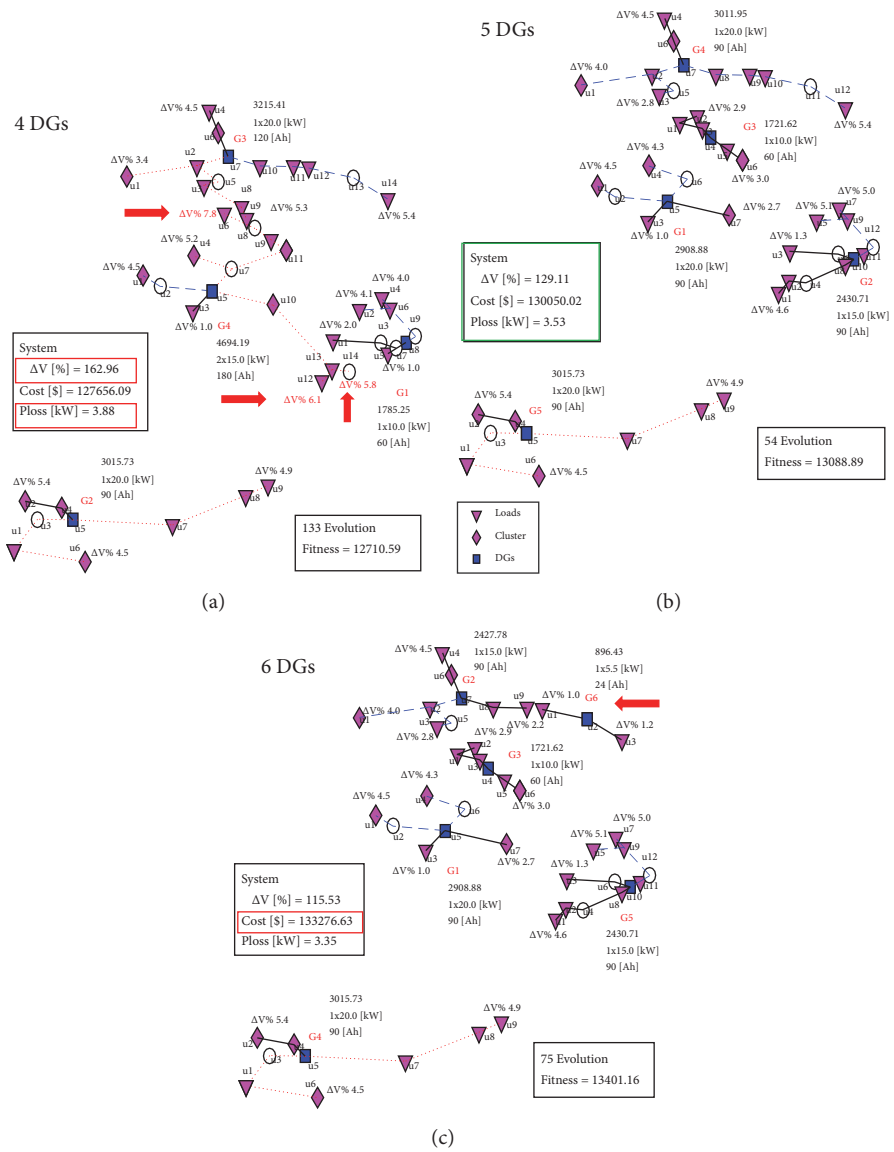

Figure 5: Results for CM2: (a) centralized system, (b) GA-PSO optimal result, and (c) decentralized system.

Table 5: GA-PSO vs centralized/decentralized models.

	Centralized	*GA-PSO*	*Decentralized*
CM1			
DG units	3	4	5
Ploss [kW]	2.30	1.83	1.55
Total Cost [$]	91759	95232	100157
Quality Issues	4	0	0
CM2			
DG units	4	5	6
Ploss [kW]	3.88	3.53	3.35
Total Cost [$]	127656	130050	133277
Quality Issues	3	0	0

Table 6: GA-PSO versus single objective/standard operators.

	Single Objective	*GA-PSO*	*Std. Operators*
CM1			
Ploss [kW]	1.81	1.83	2.20
Total Cost [$]	106693	95232	113651
Installed Capacity [kW]	70	60	65
CM2			
Ploss [kW]	3.51	3.53	9.21
Total Cost [$]	142656	130050	160483
Installed Capacity [kW]	95	85	85

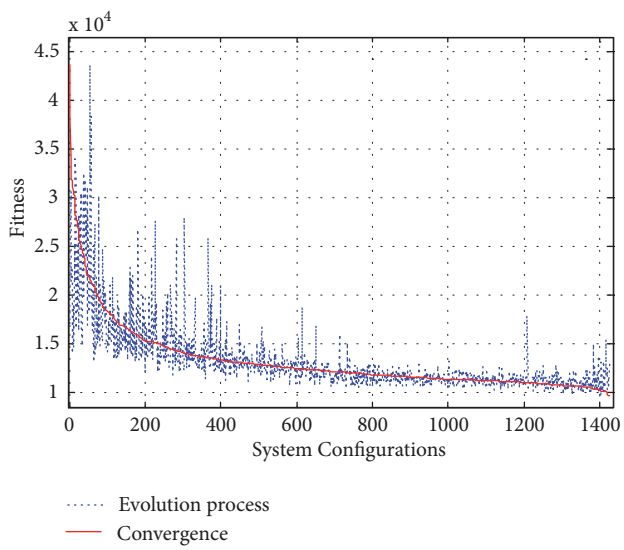

Figure 6: GA-PSO convergence curve.

This hybrid scheme was successfully applied to design isolated systems with distributed photovoltaic generation. Although the problem is multiobjective, the GA-PSO approach provided satisfactory configurations to feed all users with energy under power quality requirements. We can say that the results belong to a space of solutions that is bounded from above by a totally centralized system and from below by a totally decentralized one, where the desired balance between cost and efficiency is kept.

Considering that the planning of this type of systems has many possible solutions and optimization goals, this hybrid scheme can be the basis for other design criteria and to implement a second optimization stage regarding the management of energy and optimal operation considering reliability indices [25]; see, for example, [26].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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