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NON-DOMINATED

SORTING GENETIC ALGORITHM-II ARRANGEMENTS FOR OPTIMAL ELECTRICAL DISTRIBUTION NETWORKS RECONFIGURATION

ARREGLOS AL ALGORITMO GENÉTICO DE CLASIFICACIÓN NO DOMINADA-II PARA LA RECONFIGURACIÓN ÓPTIMA DE REDES DE DISTRIBUCIÓN ELÉCTRICA

Gustavo Crespo Sánchez[1]
E-mail: gcsanchez@ucf.edu.cu
ORCID: https://orcid.org/0000-0003-0850-197X
Ignacio Pérez Abril[2]
E-mail: iperez@uclv.edu.cu
ORCID: https://orcid.org/0000-0001-9547-6615
[1]Universidad de Cienfuegos "Carlos Rafael Rodríguez". Cuba.
[2]Universidad Central "Marta Abreu" de Las Villas. Cuba.

ABSTRACT

Radiality constraint typically increases genetic algorithms complexity considering that distribution network reconfiguration is – by nature – non-differentiable, mixed integer and highly complex combinatorial. Genetic Algorithms' potentialities can be seized when coding is enough efficient. Paper presents non-dominated sorting genetic algorithm-II arrangements, implemented in MatLab to solve optimal electrical distribution networks reconfiguration. Initial population is created randomly by using a heuristic approach and genetic operators for generating feasible individuals in every genetic evolution stage which besides are adapted with graph theory help for transforming initial population's infeasible individuals that not satisfied radiality constraint, as well as for avoiding new infeasible individual's generation and thus, sidestepping the boring mesh check and reducing search space and computational burden. Unlike previous authors that employed an integer-composed chromosome that directly selects a single branch to open from each fundamental loop vector as well as modified genetic operators, the algorithm's arrangements and a new coding used that ensures chromosome viability for all gene values has been the employed approach. That way, crossover and mutation do not need special genetic operators. Proposal efficacy has been tested with 33-bus and 70-bus test systems and results are promising and better than precedent proposals.

Keywords: Distribution systems, genetic algorithms, network reconfiguration, NSGA-II arrangements, optimization problem.

RESUMEN

La restricción de configuración radial generalmente aumenta la complejidad de los algoritmos genéticos considerando que la reconfiguración de redes de distribución es, por naturaleza, no diferenciable, entera mixta y combinatoria altamente compleja. Las potencialidades de los algoritmos genéticos se pueden aprovechar cuando la codificación es lo suficientemente eficiente. El artículo presenta arreglos del algoritmo genético de clasificación no dominada-II implementado en MatLab para resolver la reconfiguración óptima de redes de distribución eléctrica. La población inicial se crea aleatoriamente mediante el uso de un enfoque heurístico y operadores genéticos para generar individuos factibles en cada etapa de evolución genética que, además, se adaptan con la ayuda de la teoría de grafos para transformar los individuos no factibles de la población inicial que no cumplieron con la restricción de configuración radial, así como para evitar la generación de nuevos individuos no factibles y por lo tanto, eludiendo el tedioso chequeo de la malla y reduciendo el espacio de búsqueda y la carga computacional. A diferencia de autores anteriores que emplearon un cromosoma compuesto por números enteros que selecciona directamente una sola rama para abrir en cada vector de lazo fundamental, así como operadores genéticos modificados, el enfoque empleado utiliza los arreglos realizados al algoritmo y una nueva codificación que garantizan la viabilidad cromosómica para todos los valores genéticos. De esa forma, el cruzamiento y la mutación no necesitan operadores genéticos especiales. La eficacia de la propuesta se probó con sistemas de prueba de 33 y 70 barras y los resultados son prometedores y mejores que las propuestas precedentes.

Palabras clave: Algoritmos genéticos, arreglos al NSGA-II, problemas de optimización reconfiguración de redes, sistemas de distribución.

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INTRODUCCIÓN

Optimal Distribution Network Reconfiguration problem consists of identifying the best radial topology by changing feeder topological structure opening sectionalizing (normally closed) and closing tie (normally open) network switches. Switching are performed with the aim of finding a radial operating configuration that optimizes certain objectives while satisfying all the operational constraints as well as all loads are energized without islanding of any node(s). Network reconfiguration is subject to other technical and operational constraints, such as radiality, node voltage limits, branch current capacity limits, and the first and second Kirchhoff's laws (active and reactive power balance). Besides this typical formulation, network reconfiguration can also be performed primarily to improve the voltage levels, to maintain or enhance network reliability, to isolate faults more quickly, and to help prepare plans for preventive maintenance actions (Guimaraes et al., 2004). Distribution network reconfiguration is highly complex, combinatorial, non-differentiable optimization problem due to the large number of discrete switching elements. In addition, radiality constraint typically introduces additional complexity in large-sized distribution networks reconfiguration (Swarnkar et al., 2011). Obviously, greater switches number is, greater possibilities are for reconfiguration and better effects D.A.

Literature shows an extensive research work carried out in network reconfiguration area. Researches can be generally classified into conventional approaches and artificial intelligence (AI)-based approaches. Merlin A. and Back H., 1975 were the first to report a heuristic method for distribution system reconfiguration to minimize line losses. Later some other conventional approaches (Goswami et al., 1992) were developed, which include heuristic and classical optimization techniques. In Artificial Intelligence-based approaches area; (Nara et. al., 1992) introduced a genetic algorithm (GA) technique for reconfiguration of RDS with minimum loss. Later various Genetic Algorithm-based methods (Gomes et al., 2005) were developed for network reconfiguration. In fact, most of algorithms in literature are based on heuristic search techniques, using either analytical or knowledge-based engines. Several meta-heuristic techniques have been proposed to solve reconfiguration problem for loss minimization. Some of them applied genetic or evolutionary algorithms for loss minimization (Mendoza et al., 2006 and Gupta et al., 2010). Lately some other initiated-by-a-defined-individuals-number stochastic based search techniques (tentative solutions) as simulated annealing (Parada et al., 2004), taboo search algorithm (Zhang et al., 2007), ant colony optimization (Falaghi et al., 2009), particle swarm

optimization (Li et al., 2008), (Abdelaziz et al., 2009), and so on, have tried to solve distribution network reconfiguration problem. When network reconfiguration problem is solved by these techniques, one of principal difficulties is radiality constraint, which ensures network radial topology with all nodes energized. Radiality constraint not only creates difficulties in initial population formation but also during intermediate evolutionary process stages. An efficient codification of these meta-heuristic techniques has remained without perfect solution for many years (Swarnkar et al., 2011). Mendoza et al., 2006 proposed a new codification strategy and accentuated crossover and directed mutation as novel genetic operators that restricted the search space (population) and diminished drastically computational time as well as minimized memory requirements. They constructed a reduced initial population of feasible individuals which is created through the branches that form "system loops." Proposed methodology creates feasible topologies to identify system fundamental closed loops in order to originate radial topologies by creating individuals guided through fundamental loops vector. Enacheanu et al., 2008 used matroid and graph theories. Swarnkar et al., (2011) proposed a codification based upon graph theory fundamentals, which not only restricts the search space but also avoids tedious mesh checks. Proposed codification guarantees to generate only feasible radial topologies all times and is computationally efficient (Nunes Aires, 2013). Proposed Single and Multiple Link Exchange algorithms. Both insert and remove branches from network, the first one by one and the second multiple ones although – given the complexity exponential increase as branches number to insert and remove at a time increases – algorithm restricts itself to two branch exchange at a time. They considered that all branches could be removed, as long as restrictions are fulfilled. Process ends in both cases, when the least losses or optimal configuration is found. For active power losses calculation, it is necessary that a load flow be carried out in each reconfiguration.

The Non-dominated sorting genetic algorithm-II (NSGA-II)'s arrangements and a new coding used, implemented in MatLab, creates randomly initial population for genetic algorithm by using a heuristic approach and genetic operators for generating feasible individuals during initialization, crossover and mutation are modified and adapted with the graph theory's help for transforming initial population's infeasible individuals which not satisfied radiality constraint as well as for avoiding infeasible individual's generation during each stage of the genetic evolution. Although procedure steps for obtaining feasible individuals as well as fundamental loops system concept's employment is very similar to one used by other authors

(Gupta et al., 2010), (Swarnkar et al., 2011), (Mendoza et al., 2006), coding proposed is completely and absolutely new and newfangled and avoid utilizing either of modified genetic operators: Accentuated crossover and directed mutation (Gupta et al., 2010), or modified crossover and mutation (Swarnkar et al., 2011).

MATERIALS AND METHODS

In conventional Genetic Algorithms (GA), initial population that is randomly created, consists of a large number of infeasible individuals (violate radial constraint), particularly in medium and large distribution networks. In the proposal, these infeasible individuals are transformed into feasible ones using graph theory. Fundamental loops are determined for mesh network by closing all tie switches. Fundamental loops number in meshed network is equal to system tie switches number and is given by the relationship:

$$L = E - N + 1 \qquad (1)$$

Where:

E: Total elements number.

N: Total network nodes number.

Therefore, chromosome length for genetic algorithm is L. Each gene on a chromosome, denoted by a real number, will be the switch that will be open to maintain a feasible radial configuration.

Proposal changes genetic operators, "accentuated crossover" and "directed mutation" proposed by [15] to generate feasible individuals during initialization, crossover, and mutation. "Loop vectors", "common branch vectors" and "'prohibited group vectors" are also employed to avoid infeasible individuals' generation during each genetic evolution stage. Steps to obtain feasible individuals are:

1. Obtain all meshed network fundamental loops. Loop vectors L_k are created, containing the set of elements of the kth fundamental loops $k = 1, 2, \dots, L$

2. Determine all common branch vectors, C_{ij} that contain the set of common elements between two loop vectors L_i and L_j.

3. Determine all prohibited group vectors (set of common branch vectors) $R_{m1, m2, m3\dots}$, which isolate the main node(s) $m_1, m_2, m_3 \dots \dots$ of the distribution network.

4. Let Z_k be the kth gene of a chromosome, then for this chromosome to be feasible, following rules must be satisfied:

Rule 1: Each element X_k must belong to the loop vector L_k.

Rule 2: Only one branch can be opened on each common branch vector.

Rule 3: In each prohibited group vector composed of m common branch vectors, only $m - 1$ common branch vectors can be opened.

Rule 1 avoids any node isolation located on the distribution network perimeter, while Rule 2 and Rule 3 avoid node isolation inside distribution network. Therefore, when encoding individuals, these three rules ensure distribution network radial topology without forming islands of any one node(s). In general, genetic chromosomal coding in real numbers can be defined as: $Z_1 \in L_1$ $Z_2 \in L_2 \dots \dots \dots Z_k \in L_k \dots \dots Z_L \in L_L$

Problem Formulation

Proposed method formulates distribution networks reconfiguration as a multi-objective optimization problem that pursues optimal set of branches selection to open in order to obtain the minimum system operating cost and the maximum voltage in load nodes. Solutions are subject to being feasible radial configurations.

Independent Variables

Problem's independent variables, represented by array x, are the branches set that must be open to obtain a radial configuration for the distribution system. For a meshed network of N nodes and M branches, the branches number to be open in order to obtain a radial configuration is equal to the fundamental loops number L (Equation 1).

Constrains

The main problem limitation is that any reconfiguration solution must be a radial circuit. In order to fulfill this constraint, meshed network graph must be examined to determine loop vectors L, common branch vectors C, and prohibited group vectors R N. (Gupta et. al., 2010). Each loop vector L_k contains the branches set of the kth graph fundamental loop. Furthermore, each common branches vector $C_k(i,j)$, is the branches set at the loop vectors intersection L_i and L_j. On the other hand, if n is a main node set, prohibited group vector $R_k(n)$ is the m vectors common branch set which, if all are open, isolate the node set from the circuit. In that way, if x is the branches set to be open, following three rules stated by (Gupta et. al., 2010) must be met to obtain a feasible radial configuration (Viewed in the steps to obtain feasible individuals).

Objective Functions

Although other objective functions can be considered, in essence proposed optimization problem can be formalized by means of two objective functions: minimum system operation cost f₁(x) and maximum load nodes voltage f₂(x).

System operation cost is mainly related to energy losses cost in network conductors. Energy losses variable costs as well as a variable daily load demand are considered in the proposed method.

$$f_1(x) = \sum_{k=1}^{24} C_K \Delta P_K(x) \Delta t_K \qquad (2)$$

Where:

C_K ($/kWh) Energy cost in hour k,

$\Delta P_K(X)$: Network power losses in hour k and in every $\Delta t_K = 1$ hour.

For comparison purposes with literature, energy cost factors used were taken from reference (S. S. F. Souza et al., 2016).

Network power losses $\Delta P_K(x)$ are variable for different load states. Again, a daily load variation curves set is used for residential $K_r(t)$, commercial $K_c(t)$, and industrial $K_I(t)$ customers, to represent loads variability. Curves are used for both active and reactive load. For instance, if load at node i is represented by a residential-type curve, load at this node at hour k is $(P_i + jQ_i) \cdot K_r(t)$, where P_i and Q_i are maximum loads at node i.

For convenience, at-load-nodes voltage maximization can be expressed as negative maximum voltage minimization, thus, second objective function is defined by:

$$f_2(x) = -\max|V_{i,k}(x)|$$

(3)

Where $\left(1 \le i \le N_1 \le i \le N\right)$ y $\left(1 \le k \le 24\right)$

Voltages and power losses determination for different load states is achieved by a load flow function.

Optimization Algorithm

Among most successful multi-objective optimization methods are Non-Dominated Sorting Genetic Algorithm family among which is the NSGA-II. Like every genetic algorithm, a particular problem resolving by NSGA-II implies some adaptations and certain algorithm parts reprogramming. In this case, real coding algorithm NSGA-II implemented in MatLab (Seshadri, 2012). Has been adapted for solving electrical network reconfiguration. Proposed method was executed on a DESKTOP-B29S0MC Intel(R) Core(TM) i5-8350U CPU @ 1.70GHz, 1.90 GHz computer with 8.00 GB (7.86 GB usable) Installed RAM.

In order to obtain viable radial system configurations, branches selection to open is subject to compliance with three rules, which have been explained above. First Mendoza et al. (2006) and later Gupta et al. (2010) employed an integer-composed chromosome that directly selects a single branch to open from each fundamental loop vector. Modified genetic operators to generate feasible individuals during initialization, crossover, and mutation were used by them. These operators transform an infeasible chromosome to obtain a feasible one. Instead, using a coding that ensures chromosome viability for all gene values have been the employed approach in proposed method. That way, crossover and mutation don't need special genetic operators.

Chromosome Coding

In the proposal, chromosome is represented by a real values (genes) array **z**, where each value Z_K (0-≤ Z_K ≤ 1), determines X_j problem independent variable (kᵗʰ branch to open). However, independent variables determination depends on sequence in which genes **z** are decoded in the **x** selected branches set. The procedure is the following:

1. All branches are closed and available to open.

2. For all Z_k genes.

3. Available branches set in fundamental loop vector L_k (domain of X_k) is determined by:

$$domain = find\left(üüüüü \quad \left(L_k\right)\right) \qquad (4)$$

a) Corresponding branch X_k is selected from the available domain by:

$$L_k\left(domain\left(1 + round\left(Z_k\left(length(domain) - 1\right)\right)\right)\right) \quad (5)$$

b) Selected X_k branch is open and marked as unavailable for further selection.

c) A common branch vector containing an open branch will be marked as open and all its branches will be marked as unavailable for further selection.

d) All branches of a prohibited group vector with all but one open common branch vector will be marked as unavailable for further selection.

Instead of encoding variables as an integer, which is logical, because they correspond to branches number, proposal encodes variable as a real number between 1 and 0 $(0 < X_i < 1)$ where zero is the first prohibited loop switch and one (1) the last one. X_i is an arbitrarily selected value. This avoids making Gupta's modifications [19]. Then, by simple linear expression, the closest number to the real number obtained is searched (Equation 5).

An arrangement called "isvar" was made that identifies if that variable is available to work with and at the beginning, all of them were given a value one (1), i.e., all values could be selected. If variable state is zero (0) it means that switch is open and if it is one (1) it means that it is closed. Each value of X_i is the real value generated randomly for i variable (i.e., for the first variable, it is X_1, so "vars" would mean: What are loop variables being analyzed?). For variable i it is the fundamental loop$i$. But not all possible variables are analyzed, but only those that $isvar = 1$.

Available variables are checked. Which ones that have $isvar = 1$ are searched, that at the beginning are all of them, because to all is assigned a value of 1.

Illustrative Example

As illustrative example, procedure to determine X$_j$ problem independent variable (kth branch to open), is shown below:

For the First Fundamental Loop

For example, in 33-bus test distribution systems, for the first loop, there are ten variables that are switches 2, 3, 4, 5, 6, 7, 33, 20, 19 and 18. For the 10 variables, $isvar = 1$, thus, all are available. Figure 1 depicts 33-bus test distribution system loop 1's switches and branches.
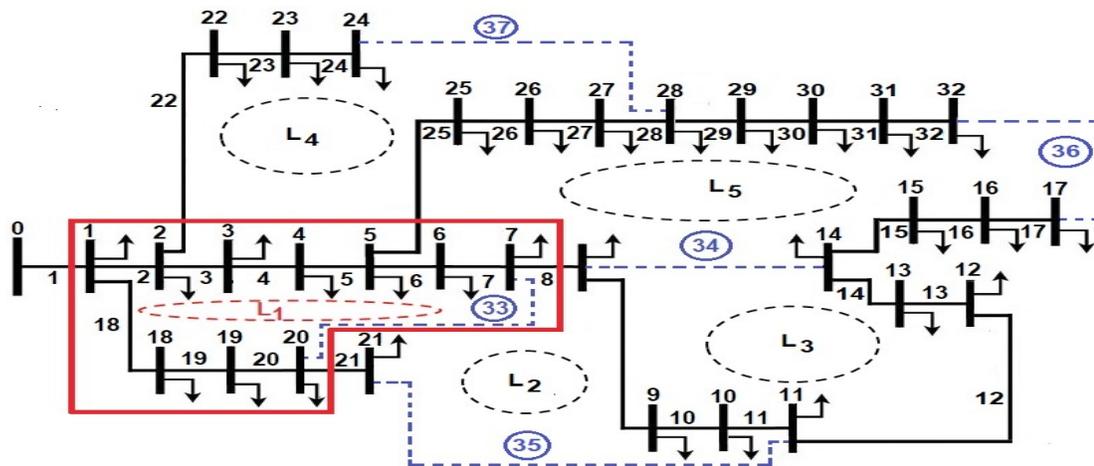

Figure 1. 33-bus test distribution system's Loop 1 (L1). Source: own elaboration

Figure 2 shows loop 1's each switch number, all of them with *isvar = 1* that mean they are all closed and could be selected. Besides, variables number (vars = 1 …10) from which through equation (1 + X$_i$ (variables number) - 1) is determined the switch selected to open. In addition, switch selection to be open is shown for 0, 1, 0.5 values of X$_i$.

			Loop 1 Switches									
		Switch number	2	3	4	5	6	7	33	20	19	18
		isvar	1	1	1	1	1	1	1	1	1	1
		vars	1	2	3	4	5	6	7	8	9	10
X_i	0	$1 + round(X_i(length\,(vars) - 1))$	1									
X_i	1	$1 + round(X_i(length\,(vars) - 1))$										10
X_i	0.5	$1 + round(X_i(length\,(vars) - 1))$						7				

Figure 2. Procedure to select the switch to be open for 0, 1, 0.5 values of X$_i$. Source: own elaboration

Vars = 1 … 10

If variable state is zero (isvar = 0), it means that switch is open.

Variable X_i comes with a value. Therefore: = 1 + X_i (variables number) – 1) and that value is rounded.

- If X_i = 0 it would be: = 1 + 0 ((10) – 1) = 1 + 0 = 1. The first switch would be selected which is number 2.

- If Xi = 1 it would be: = 1 + 1 ((10) – 1) = 1 + 9 = 10. The last switch would be selected which is number 18.

  If a X_i intermediate value were obtained, with equation 1 + round (X_i (length (var) – 1)), variable with integer number (switch) with which it is going to work is selected (because it is rounded) and that value is assigned to loop array, which selects which variable is.

  Once switch to be opened has been selected, start of that variable is marked zero (0) to indicate that this switch opened but also that it can no longer be used.

- If Xi = 0.5 it would be: = 1 + 0.5 ((10) – 1) = 1 + 4.5 = 5.5 ≈ 6. Sixth switch would be selected which is number 7.

For example, in Figure 3, if switch 18 is that opens: stat (18) = 0 to indicate that this variable (switch) opened; isvar (18) = 0 so that variable cannot be used anymore. Thus, switch 18 can never be selected again. This avoids an infeasible variable.

	Loop 1 Switches									
Switch number	2	3	4	5	6	7	33	20	19	18
isvar	1	1	1	1	1	1	1	1	1	**0**
vars	1	2	3	4	5	6	7	8	9	

Figure 3. Switch 18 is selected to open. Source: own elaboration

MatLab Arrays

function stat = decode(self,x)

    x(x < 0) = 0;

    x(x > 1) = 1;

    M = size(self.branches,1);

    MT= size(self.lnodes,1);

    stat = ones(MT,1);

    isvar = zeros(MT,1);

    isvar(1:M) = 1;

    for i = 1:length(x)

% select possible branches to be disconnected in the loop

    loop = self.loops{i};

    vars = find(isvar(loop));

% select branch

```
    k = loop(vars(1 + round(x(i) * (length(vars) - 1))));
```

% the selected branch is disconnected

```
    stat(k)  = 0;

    isvar(k) = 0;
```

Genetic Operators

Taking into account that chromosome is always feasible for real numbers within limits $0 < X_i < 1$, there is no need to use special genetic operators as already stated.

In proposed method, 60% of offspring population is obtained by crossover, for which a scattered crossover operator is used. Operator creates a set *u* half the chromosome size, uniformly randomly sampled. The first offspring selects genes from the first parent that are not in *u* and genes from the second parent that are in *u*. The second descendant inverts selection. Remaining 40% offspring population is obtained by mutation, for which a uniform mutation operator is used. Operator mutates 2% genes on the uniformly randomly sampled chromosome. Each gene mutates by a normally distributed random number using a 0.1 mutation step.

Objective Functions Calculations

A special NSGA-II part that must be reprogrammed to solve the presented problem is a procedure for computing objective functions f1(x) and f2(x). This procedure, named Evaluate_objectives (x), is called by NSGA-II algorithm each time a new individual is produced by crossover or mutation. The parameter (x) which passed to this procedure is the chromosome.

Procedure developed for Evaluate_objectives (x), executes following steps:

1. From x, determines branches to be open and are opened.
2. Circuit analysis is performed by a load flow program.
3. Two objective functions are evaluated: $f_1(x)$ and $f_2(x)$.

RESULTS AND DISCUSSION

Table 1 shows a comparison of 33-bus test system obtained results (Mahdavi et. al., 2021) with other methods.

Table 1. Comparison of 33-bus test system obtained results with other methods

Methods	Run time (s)	Open switches	Initial Losses (kW)	Losses after Reconfiguration (kW)
Based on optimal power flow using benders decomposition (J. A. Taylor et al., 2012).	0.11	7, 9, 14, 32, 37	202.54	139.55
Convex models using quadratically programming (J. A. Taylor et al., 2012).	0.21	7, 9, 14, 32, 37	202.7	139.55
Efficient simulated annealing (Y. J. Jeon et al., 2002).	0.34	7, 9, 14, 32, 37	202.7	139.55
Simulated annealing algorithm (Y. J. Jeon et al., 2002).	0.3	7, 9, 14, 32, 37	202.7	139.55
Mixed-integer linear program model (F. Llorens Iborra et al., 2012).	1.0	7, 9, 14, 32, 37	202.68	139.55
Convex models using quadratically constrained Program (J. A. Taylor et al., 2012).	1.43	7, 9, 14, 32, 37	202.7	139.55
New branch Exchange Heuristic algorithm (F. V. Gomes et al. 2005).	1.66	7, 9, 14, 32, 37	202.68	139.55
Discrete ascent optimal programming (F. V. Gomes et al. 2005).	1.99	7, 9, 14, 32, 37	202.68	139.55

Fast reconfiguration considering loss minimization (H. P. Schmidt et al., 2005).	0.01	7, 9, 14, 28, 31	194.53	142.03
Fast reconfiguration considering loss minimization D. Shirmohammadi et al., 1992).	0.14	7, 10, 14, 32, 31	202.68	140.26
A new approach using optimum power flow and sensitivity analysis (F. V. Gomes et al. 2006).	1.99	7, 10, 14, 32, 37	202.68	140.26
Proposed	4.31	6, 9, 14, 36, 37	139.46	96.39

Source: own elaboration

Table 2. Comparison of 70-bus test system obtained results with other methods.

Methods	Average computing time (s)	Number of global optimal reached in 100 runs	Open switches	Real power loss (kW)
Hybrid genetic particle swarm optimization algorithm (C. Zhang et al., 2007).	43	100	14, 59, 62, 70, 71	99.70
Simulated annealing (H. D. Chiang et al., 1990)	36	95	14, 57, 62, 70, 71	99.70
Enhanced genetic algorithm-based fuzzy multi-objective approach Y. C. Huang (2002).	13	97	13, 59, 70, 71, 74	122.90
Adaptive genetic algorithm in fuzzy framework (N. Gupta et al., 2010).	8	100	15, 58, 62, 70, 71	99.60
Proposed	7.89	57	12, 56, 63, 69, 70	53.88

Source: own elaboration

Both results shown in the above tables show that non-dominated sorting genetic algorithm-II arrangements and coding proposal application provides a promising tool for optimal electrical distribution networks reconfiguration taking into consideration that unlike researchers precedent the proposal neither does not need to modify the answer when individual's generation is infeasible nor for avoiding new infeasible individual's generation. In addition, the use of special genetic operators is not necessary. Proposal does not make modifications and get reducing search space and computational burden.

CONCLUSION

An efficient coding of meta-heuristic techniques has remained without perfect solution for many years. The coding proposal is adapted by using graph theory help for generating feasible individuals as well as for transforming each infeasible individual in feasible (radial networks), in each stage of the genetic evolution. In addition, considering that chromosome is always feasible for real numbers within limits $0 < X_i < 1$, there is no need to use special genetic operators as already stated.

Unlike (Mendoza et. al., 2006) new coding proposal not only search to isolate external nodes but also internal ones during feasible individual's generation. In contrast to (Gupta et. al., 2010) which modify the answer when this is infeasible by executing an accentuated crossover process to make it feasible, proposal does not make modifications. In the Non-dominated sorting genetic algorithm-II arrangements proposed, no genetic algorithm modification needs to be made. Once switch that will be open is selected, it will no longer can be used, thus, variant number to be used is reduced considerably. In addition, infeasible variants are avoided, therefore computational time is reduced.

In contrast to authors mentioned above, that employed an integer-composed chromosome that directly selects a single branch to open from each fundamental loop vector as well as modified genetic operators, the use a coding that ensures

chromosome viability for all gene values have been employed. That way, crossover and mutation don't need special genetic operators.

Non-dominated sorting genetic algorithm-II arrangements and coding proposal application results, implemented in MatLab show that proposal provides a promising tool for optimal electrical distribution networks reconfiguration. Other objective functions can be considered without any additional computational burden. Proposal effectiveness has been tested with 33-bus and 70-bus test distribution systems and results are a promising tool for optimal electrical distribution networks reconfiguration and better than precedent proposals.

Future Work

Notwithstanding previous results, author's work continues on coding perfecting and improvement for genetic algorithms used in optimal distribution network reconfiguration and especially, on the improvement of NSGA-II algorithm, for its future use as an effective method in network reconfiguration.

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