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Distribution network reconfiguration using a genetic algorithm with varying population size

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ABSTRACT

Genetic algorithm (GA) has been shown to be an effective way to solve the complex combinatorial, and constrained non-linear mixed integer optimization problem of distribution network reconfiguration. Extensive work has been done in the literature to efficiently apply GA to the reconfiguration problem. Nonetheless, to date, all the previous work in this area have presupposed that the GA population size should remain constant throughout the evolution of the search process. In this paper, we propose the application of a genetic algorithm with variable population size (GAVAPS) to the reconfiguration problem. We demonstrate that allowing the population size to adaptively grow and shrink according to the status of the GA search can allow for a more efficient solution, compared to standard genetic algorithm.

1. Introduction

Distribution network reconfiguration is the process of changing the topological structure of distribution feeders by updating the open/close status of the network sectionalizes and tie switches. Reconfiguration is an effective way to improve the performance of power distribution networks. By updating the switches open/close status, a distribution network reconfiguration algorithm changes the topological structure of distribution feeders in a way that optimizes the system performance while satisfying its operational constraints. Given the nonlinear characteristics of the distribution system constraints, as well as the large number of system switching elements, the distribution network reconfiguration problem is a complex, nonlinear and constrained mixed-integer optimization problem where integer variables represent the system switches and continuous variables represent the distribution network. The complex nature of the distribution network reconfiguration problem, makes it prohibitive to adopt most of the exact optimization methods to solve it [1]. On the other hand, heuristic techniques have been shown to be particularly suitable to handle the complex optimization problem of distribution system reconfiguration. In particular, extensive work has been done to efficiently apply genetic algorithm (GA) to the reconfiguration problem (see for instance [1–4] and references therein). Nonetheless, to date, all the previous work in this area have presupposed that the GA population size should remain constant throughout the evolution of the search process. In this paper, we propose the application of a genetic algorithm with variable population size (GAVAPS) to the reconfiguration problem. We demonstrate that allowing the population size to adaptively grow and shrink according to the status of the GA search can allow for a more efficient solution, compared to standard genetic algorithm (SGA) that maintains a constant population size.

2. Distribution network reconfiguration by GAVAPS

The theory of GAVAPS was originally introduced to the field of Evolutionary Computations in [5]. Reference [5] presented a non-elitist GAVAPS to maximize non-linear multi-modal mathematical functions. In this paper, we build on the work in [5] and propose an elitist GAVAPS to solve the power distribution network reconfiguration problem. The proposed GAVAPS searches for a solution to the reconfiguration problem using a population that evolves through successive generations. Each individual in the population represents a possible solution and is termed a "chromosome". A chromosome is coded as a genetic string containing the locations of open switches in the power distribution network. Each chromosome is assigned a lifetime parameter at its creation. At each generation, an offspring population is created from the current population using genetic selection, mutation and crossover operators. Chromosomes in the current population, whose age (i.e., the number of generations the chromosome has been alive) does not exceed their lifetime parameter, are passed to the next generation along with the offspring population. Chromosomes whose age exceed their lifetime parameter die and leave the genetic pool.

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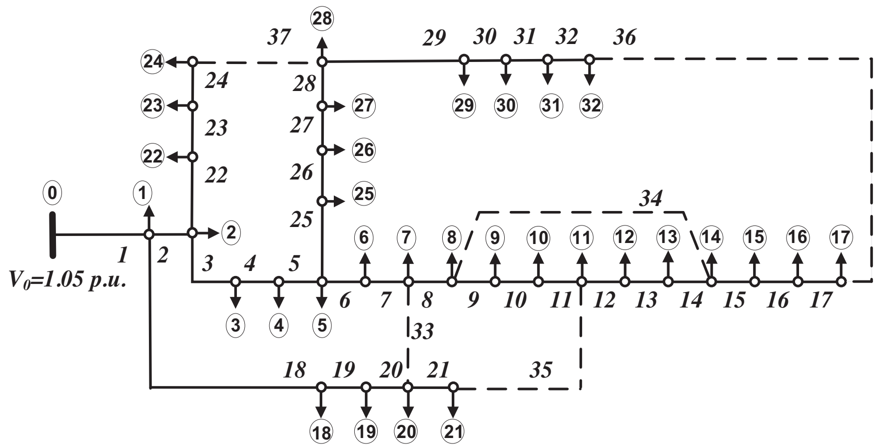

Fig. 1. Distribution test system [6], (V_{base} = 12.66 kV and S_{base} = 10 MVA).

The generations succeed one another until the search converges or a maximum number of fitness function evaluations is attained.

The implementation procedures of the proposed GAVAPS process can be given as follows; at generation t; *Step 1*: determine the size of the offspring population $N_{offspring}$ as

$$N_{offspring}(t) = \max(\text{round}(N(t) * \rho),\ \alpha) \quad (1)$$

where $N(t)$ is the size of the population at generation t, ρ is the reproduction rate parameter, and α is the elite count parameter. *Step 2*: the first α chromosomes in the offspring population will be the elite children selected directly from the current population based on their fitness values. *Step 3*: if $N_{offspring}(t) > \alpha$, the subsequent β chromosomes in the offspring population will be crossover children,

$$\beta(t) = \text{round}((N_{offspring}(t) - \alpha) * \mu) \quad (2)$$

and μ is a crossover fraction parameter. Similarly, the remaining γ chromosomes will be mutation children;

$$\gamma(t) = N_{offspring}(t) - \alpha - \beta(t) \quad (3)$$

Each chromosome in the current population can be chosen to parent crossover and mutation children with equal probability and irrespective of its fitness value. *Step 4*: for each of the generated crossover and mutation children determine the fitness value (based on the system power losses) and feasibility (based on the constraints satisfaction) by solving the load flow problem. A mutation or crossover child is included in the offspring population, only if it passes the feasibility tests. Otherwise, the respective crossover or mutation operator is repeated to generate a feasible alternative. *Step 5*: selective pressure is applied through the chromosome lifetime parameter. The lifetime parameter for each chromosome c in the offspring population is calculated according to

$$Lifetime(c) = \min\left(MinLT + \eta\frac{fitness(c)}{AvgFit},\ MaxLT\right) \quad (4)$$

where *MinLT* and *MaxLT* are the minimum and maximum allowable lifetime parameters, $\eta = 0.5(MaxLT - MinLT)$, *fitness (c)* is the fitness of the cth chromosome in the offspring population and *AvgFit* is the average fitness value of the current population. *Step 6*: increase the age of each chromosome in the current population by one. *Step 7*: form the population for generation $t+1$ to compromise the offspring population as well as all the chromosomes in the current population t whose age did not exceed their lifetime parameter and that are not present in the offspring population.

Table 1
Comparison of SGA and GAVAPS results.

Initial population size	10	15	20	25	30
Average number of power flows					
SGA	435	591	787	901	1114
GAVAPS	310	333	383	385	427

3. Test and results

The proposed GAVAPS for power distribution network reconfiguration was tested on the well-known Baran reconfiguration test system, shown in Fig. 1. In this work, we investigate a single-objective loss reduction problem formulation. However, other possible formulations may be readily adopted with the proposed GAVAPS. The performance of the proposed approach has been compared to SGA. In order to allow for an objective comparison, the GA parameters, codification as well as genetic mutation and crossover operators were identical for both SGA and GAVAPS. Mutation and crossover operators similar to the ones presented in [3] and [1], respectively, have been adopted in this work. On the other hand, the genetic selection operator, which represents one of the main differences between the proposed GAVAPS and SGA, was different. While in GAVAPS all the individuals in the current population have equal probability to parent mutation and crossover children (i.e., irrespective of their fitness), in SGA the selection of parents is based on the fitness value (i.e., individuals of higher fitness have higher probability of being selected as parents for mutation and crossover children). Initial population sizes of 10, 15, 20, 25 and 30 were tested with both SGA and GAVAPS. In case of SGA, the size of initial population remained constant throughout the evolution of the GA search. In the case of GAVAPS, a reproduction rate of 0.4, a minimum and maximum lifetime parameters of 1 and 7, respectively, were applied and the population size evolved through the search process. A crossover fraction of 0.8 and an elite count of 2 were applied for both SGA and GAVAPS. Populations were initialized at random, and 50 independent runs were performed on each initial population size. The number of power flows required were averaged over these 50 runs giving the reported results. The best solution presents 114.271 kW losses, with the following branches open: 7, 12, 31, 35 and 37. Table 1 shows the average number of power flow evaluations required in each case studied to reach the best configuration. The results in Table 1 demonstrate that the adoption of a variable population size can significantly decrease the computational cost of the reconfiguration algorithm and allow for a better exploration of the solution space as well as less susceptibility to the initial population size. Here it is worth mentioning that the application of GAVAPS to the electric distribution network

Table 2
Comparison with previously published algorithms.

Algorithm	Proposed GAVAPS	Reference [7]	Reference [8]	Reference [4]	Reference [9]	Reference [10]	Reference [11]
Average number of power flow evaluation required	310	450	705	525	1600	640	433

reconfiguration problem is not limited to the GA process presented in Section 2. Advanced encoding and codification algorithms previously adopted with SGA (see for instance [1–4]) can be readily adopted with GAVAPS. Table 2 presents a comparison of the number of power flow evaluations required by the proposed GAVAPS with those required by other techniques available in the literature.

4. Conclusion

Existing literature investigating distribution network reconfiguration using GA have all presupposed that the GA population size should remain constant throughout the evolution of the search process. In this paper, we amend this presupposition and propose an alternative approach that allows the population size to change size adaptively through the progressing generations based on the search status. It is demonstrated that a GA of varying population size can yield lower computational costs in solving the reconfiguration problem.

References

[1] E. Carreno, R. Romero, A. Padilha-Feltrin, An efficient codification to solve distribution network reconfiguration for loss reduction problem, IEEE Trans. Power Syst. 23 (4) (2008) 1542–1551.
[2] H. de Macedo Braz, B. de Souza, Distribution network reconfiguration using genetic algorithms with sequential encoding: subtractive and additive approaches, IEEE Trans. Power Syst. 26 (2) (2011) 582–593.
[3] Y.-T. Hsiao, Multiobjective evolution programming method for feeder reconfiguration, IEEE Trans. Power Syst. 19 (1) (2004) 594–599.
[4] J. Mendoza, R. Lopez, D. Morales, E. Lopez, P. Dessante, R. Moraga, Minimal loss reconfiguration using genetic algorithms with restricted population and addressed operators: real application, IEEE Trans. Power Syst. 21 (2) (2006) 948–954.
[5] J. Arabas, Z. Michalewicz, J. Mulawka, GAVaPS – a genetic algorithm with varying population size, in: Proceedings of the First IEEE Conference on Evolutionary Computation, June, 1994.
[6] M. Baran, F. Wu, Network reconfiguration in distribution systems for loss reduction and load balancing, IEEE Trans. Power Syst. 4 (3) (1989) 1401–1407.
[7] B. Enacheanu, B. Raison, R. Caire, O. Devaux, N. Hadjsaid, Radial network reconfiguration using genetic algorithm based on the Matroid theory, IEEE Trans. Power Syst. 23 (1) (2008) 186–195.
[8] E. Romero, A. Gomez, J. Riquelme, F. LLorens, Path-based distribution network modeling: application to reconfiguration for loss reduction, IEEE Trans. Power Syst. 20 (2) (2005) 556–564.
[9] R. Srinivasa Rao, S.V.L. Narasimham, M. Ramalinga Raju, A. Srinivasa Rao, Optimal network reconfiguration of large-scale distribution system using harmony search algorithm, IEEE Trans. Power Syst. 26 (3) (2011) 1080–1088.
[10] C.-C. Chu, M.-S. Tsai, Application of novel charged system search with real number string for distribution system loss minimization, IEEE Trans. Power Syst. 28 (4) (2013) 3600–3609.
[11] C. Wang, Y. Gao, Determination of power distribution network configuration using non-revisiting genetic algorithm, IEEE Trans. Power Syst. 28 (4) (2013) 3638–3648.