Distribution Feeder Reconfiguration Considering Distributed Generators using Cuckoo Optimization Algorithm

Mohamad Amiri, Mina Sheikholeslami Kandelousi, and Mahmood Moghadasian

Abstract—In many countries the power systems are going to move toward creating a competitive structure for selling and buying electrical energy. These changes and the numerous advantages of the distributed generation units (DGs) in term of their technology enhancement and economical considerations have created more incentives to use these kinds of generators than before. Therefore, it is necessary to study the impact of DGs on the power systems, especially on the distribution networks. The distribution feeder reconfiguration (DFR) is one of the most important control schemes in the distribution networks, which can be affected by DGs. This paper presents a new approach to DFR at the distribution networks considering DGs. The main objective of the DFR is to minimize the deviation of the bus voltage, the number of switching operations and the total cost of the active power generated by DGs and distribution companies. Since the DFR is a nonlinear optimization problem, we apply the Cuckoo Optimization Algorithm (COA) to solve it. The feasibility of the proposed approach is demonstrated and compared with other evolutionary methods such as genetic algorithm (GA), and Tabu search (TS) over a realistic distribution test system.

Keywords—Cuckoo Optimization Algorithm, Distributed generator, Distribution feeder reconfiguration, Distribution networks.

I. INTRODUCTION

The reconfiguration of a distribution network is a process that alters feeder topological structure, changing the open/close status of sectionalizers and interruptors in the system. Under normal operational conditions, the objectives are avoiding excessive transformer load, conductor overheating, and minimizing abnormal voltages and at the same time minimizing the active power losses of the system. The first publication about the reconfiguration problem was presented by Merlin and Back [1]. In this paper, the global minimum is calculated starting from a meshed network. This method was later modified by Shirmohammadi and Hong in [2], where they reduced computation time by applying an efficient load flow.

Civanlar and Grainger in [3] derived a formula to estimate loss reduction using an algorithm called “branch interchange.” Other heuristic methods have been published that are principally based on switch interchange, sets of rules to determine open/close status of sectionalizers, and linearization of the objective function using approximated formulas for losses evaluation as those presented in [4] and [5].

In [6], Glamocanin used quadratic programming to formulate the reconfiguration problem as a transfer problem with quadratic costs. Sarfi in [7] proposed an algorithm based on the division of a distribution network into a groups of feeders. His algorithm used a rapid heuristic technique for system division, taking into account the principal ideas proposed by [3] and [8]. McDermott [10] proposed a constructive heuristic method for the reconfiguration of minimal losses. Lopez in [11] proposes a minimal loss reconfiguration method applied to large distribution systems based on the dynamic programming approach, graph compression, and radial load flow. Finally, the same authors in [12] consider the variability demand in the reconfiguration process.

In the literature, various methods exist that employ artificial intelligence, among them, genetic algorithms (GAs). This technique bases its search mechanism on the principles of natural selection for creating a set of feasible solutions (populations). Holland in [13] was the pioneer in the use of this technique and since its inception has been applied to a wide variety of optimization problems. The algorithm structure is based in the generation of a population of individuals that represent the solutions (generation), and then these are evaluated using an objective function; the individuals that have the greatest aptitude are then selected. Finally, a new population is created using crossover and mutation operators. This allows converging to the best solution [14]–[16].

The first work that applied GA to the reconfiguration problem was developed in 1992 by Nara [17]. In spite of the excellent results, the conclusion of this paper and the study developed by Sarfi [18] pointed out the need for computers with greater processing speed. The principal trouble presented in [17] is related to the binary codification used; it identified the arc (branch) number that contains the ith open switch and identifies the switch that is normally open in this arc. That codification type can be very long, and it grows in proportion with the switch number. Also, an approximated fitness function was used to represent the system power loss.

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Nevertheless, the technological advances in computer hardware allow today the application of these methodologies with greater benefits and fewer limitations in terms of the problem dimensions and computational times involved in the population size, number of generations, and objective function evaluation.

In [19], the GA method is refined, in the reconfiguration problem, by modifying the string structure and fitness function. Here, a binary string represents only positions of the open switches in the distribution network. Consequently, the length of the string is reduced, depending on the number of open switches. The fitness function also considers constraints of the systems. An adaptive mutation process is used to change the mutation probability.

Lopez in [20] made an important contribution to the reconfiguration process using GA, with excellent results in the simulation times, when introducing graph compression, current flows analysis, current flows analysis, stochastic minimum extension trees, and diakoptic compensatory currents. All of these techniques are used to simplify the system’s model, allowing the evaluation of the objective function with less computational efforts. Also, a set of filters is introduced in order to eliminate the individuals that transgress the system operational constraints (like over-currents and voltage ranges). However, the computational efforts are still significant due to the generated random population, where many do not override the radiality and connectivity filters.

In [21], a GA technique is applied to the multiobjective reconfiguration problem. This work used the “Prüfer number” codification, to avoid a tedious “meshed check” algorithm. The crossover is applied in two points randomly selected. The single point mutation is applied, and the roulette wheel approach is used to select the rest of the individuals.

The work presented in [22] is the only one that develops a method to create a feasible population. This method is based on the concept called “path-to-node.” This scheme is based on the preliminary identification of alternative paths linking each bus to the substation. This path definition creates radial topologies for the initial population with excellent results but only using traditional genetic operators.

In this paper, a novel distribution feeder reconfiguration (DFR) approach is presented for a distribution network containing DG units. A cost-based control methodology is proposed as a proper criterion for the real/reactive-power control of the DG units of a distribution system. In the proposed DFR approach four objective functions have been considered as follows:

- The cost of the active power generated by DGs.
- The cost of the active power generated by distribution companies.
- The number of switching operations.
- The deviation of the voltage of buses.

Since the tie and sectionalizing switches and DG units are non-differentiable and nonlinear, respectively, the distribution feeder reconfiguration problem is conventionally considered a mixed-integer nonlinear programming problem. To solve such a problem, classical methods, e.g., linear programming, mixed-integer programming, quadratic programming, etc., can be applied. However, in some cases, the mentioned methods fail to provide the global minima and only reach local minima. Moreover, some classical methods cannot handle the integer problems [19]. The two foregoing shortcomings can be overcome if an evolutionary method is utilized.

It is independent of the objective function type and constraints renders. In this paper, an evolutionary optimization method, based on Cuckoo Optimization Algorithm (COA), has been utilized to solve the DFR problem.

II. MODELING OF DISTRIBUTION FEEDER RECONFIGURATION

In this section, the distribution feeder reconfiguration considering DG units has been modeled as a multi-objective, non-differentiable optimization problem.

A. Objective function

In the proposed DFR approach, the objective function consists of four terms: (i) the cost of the active power generated by the distribution companies, (ii) the cost of the active power generated by DG units, (iii) the number of switching operations, and (iv) the deviation of the bus voltage. The objective function of the DFR with its four terms has been demonstrated by the following equation:

\[
\begin{align*}
    f(\mathbf{x}) &= \sum_{i=1}^{N_{\text{sub}}} P_{\text{sub},i} \times \text{Price}_i + \sum_{i=1}^{N_{\text{sub}}} C_{P_{gi}}(P_{gi}) + \\
    &+ \sum_{i=1}^{N_{\text{sw}}} |S_i - S_{oi}| + \sum_{i=1}^{N_{\text{bus}}} |V_i - V_{\text{o, rat}}| \\
    \mathbf{x} &= [\mathbf{S}_w, \mathbf{P}_{\text{sub}}, \mathbf{P}_G, \mathbf{Q}_G] \\
    \mathbf{S}_w &= S_1, S_2, \ldots, S_{N_{\text{sw}}} \\
    \mathbf{P}_{\text{sub}} &= [P_{\text{sub},1}, P_{\text{sub},2}, \ldots, P_{\text{sub},N_{\text{sub}}}] \\
    \mathbf{P}_G &= P_{g1}, P_{g2}, \ldots, P_{gN_g} \\
    \mathbf{Q}_G &= Q_{g1}, Q_{g2}, \ldots, Q_{gN_g} \\
\end{align*}
\]

where \(N_{\text{sub}}, N_g, N_{\text{sw}}, \) and \(N_{\text{bus}}\) are the number of substations, DGs, switches and buses, respectively. \(\mathbf{x}\) is the state variable vector. \(P_{\text{sub},i}\) is the active power of the \(i\)th substation. \(\mathbf{P}_{\text{sub}}\) is the substation active power vector including active power of all substations. \(S_{wi}\) is the state of the \(i\)th switch specified in terms of on/off status, taking 0 or 1 as its value. \(\mathbf{S}_w\) is the switching state vector including state of all switches. \(\text{Price}_i\) is the electrical energy price at the \(i\)th substation. \(C_{P_{gi}}(P_{gi})\) is the cost of active power generated by the \(i\)th DG. \(\mathbf{Q}_G\) is the DGs reactive power vector including reactive power of all DGs. \(Q_{gi}\) is the reactive power of the \(i\)th DG. \(\mathbf{P}_G\) is the DGs active power vector including active power of all DGs. \(P_{gi}\) is the active power of the \(i\)th DG. \(S_i\) and \(S_{oi}\) are the new and original states.
of switch $i$, respectively. And $V_i$ and $V_{rat}$, the real and rated voltage on bus $i$, whilst $w_1$ and $w_2$ represent weighting factors.

### B. Cost model for DG units

In general, the cost of each kWh of electric energy generated by a DG unit is assumed to be composed of (i) the initial investment, including the cost of equipment, infrastructure, commissioning, etc., (ii) operation and maintenance (O&M) costs, and (iii) fuel cost [18]. This can be expressed by the following equation:

$$C_{pg}(P) = a + bP$$

where “a” and “b” are fuel coefficients [24].

### C. Constraints

System constraints consist of active power constraints of DGs, distribution line limits, distribution power flow equations, capacity margin of transformers, and radial structure of the network.

### III. BASIC PRINCIPLES OF THE COA

COA begins with an initial population, exactly the same as other evolutional algorithms. The population consists of cuckoos [23]. The population possesses some eggs that will lay them on the nest of some other host birds. Those legs that look like the host bird eggs have a chance to survive and be changed into a grownup cuckoo. The rest of the eggs are identified by the host bird and will be wiped out. The number of grownup eggs represents the suitability of nests in that region. Whatever the number of surviving and existing eggs is higher; more interests (trends) are allotted to that region. Thus a condition, in which the most number of eggs are surviving, will be a parameter that COA intends optimization [24].

All cuckoos will be at the same point of optimization with maximum similarities between their eggs and the host birds' eggs after some repetition. Also more food sources will be available there. This place possesses the most total interests and the least wiping out in eggs. Ultimate end of cuckoo search optimization algorithm (COA) is more than 95% convergence of all cuckoos toward a special point.

### IV. SIMULATION RESULTS

In this section, the COA algorithm is utilized to solve the DFR of a distribution test feeder, whose one-line diagram is given in Fig. 1. It is assumed that every branch has a sectionalizing switch. This system has three feeders and four tie switches. The tie switches and sectionalizing switches are normally open and closed, respectively.

It is assumed that there are three generators, whose specifications are given in Table I. The active power prices at each substation are 0.05, 0.045 and 0.051 $/kW, respectively.

Table II provides the simulation results carried out on the test system of Fig. 3, using MATLAB software, and includes the best and the worst solutions. Furthermore, Table I provides the simulation results based on the Cuckoo Optimization Algorithm (COA), genetic algorithm (GA), Tabu search (TS) whilst their simulation parameters are presented in the Appendix, for 300 times running of the algorithms. In Table II,
V. CONCLUSION

Issues such as environmental pollution, restructuring in electrical industry and technology advancement have resulted in an increase in the usage of distributed generators which most of the time connect to the distribution networks. Therefore, with an increase in connecting these generators to the distribution networks, it is a necessity to study the effects of these generators on distribution systems. This paper has presented an efficient approach to distribution feeder reconfiguration in presence of DG units. Due to private ownership of DG units, a cost-based compensation method has been used to dispatch DGs. The COA algorithm has been applied to find the best solution for the DFR problem. The results have demonstrated that COA has better performance than GA and TS.

APPENDIX

A. Genetic algorithm

In this paper, integer strings instead of binary coding are used to represent value of variables, and include these processes:
1. Representation and initialization.
2. Fitness function.
4. Crossover operation.
5. Mutation operation.

Simulation conditions are:
- Initial population = 1000.
- Selected population = 300.
- Mutation = 4%.
- Crossover probability = 0.2–0.3.

B. Tabu search

Tabu search is a heuristic algorithm for guiding the search to find a good solution to a combinatorial problem. It is derived from the works of Fred Glover with seminal ideas and contributions from various other sources. Tabu search has been successfully applied to obtain optimal or sub-optimal solutions to problems such as timetables, the traveling salesman and so on [25]. To apply the Tabu search algorithm to solve the DFR problem the following steps should be repeated [25]:

Step 1: Generation of initial population.
Step 2: Selection of good population and generation of the Tabu list.
Step 3: Creation of new population.
Step 4: Evaluation and selection.
Step 5: Updating the Tabu list.
Step 6: Checking the convergence.

Simulation conditions are:
- Initial population = 1000.
- Selected population = 300.
- Tabu list = 30.

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<th>Min reactive power</th>
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<th>Fuel cost</th>
<th>O&amp;M cost</th>
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