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Application of Modified Bacterial Foraging Optimization algorithm for optimal placement and sizing of Distributed Generation

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ABSTRACT

In this paper, a new approach in Bacterial Foraging Optimization algorithm is proposed to reduce the total power loss and to improve the voltage profile of the radial distribution systems, in the presence of Distributed Generation unit. The proposed method aims to modify the performance of the Bacterial Foraging Optimization algorithm. The test results obtained from Modified Bacterial Foraging Optimization algorithm are also compared and found to be better and in close agreement with the Bacterial Foraging Optimization algorithm. The achievability and convenience of the optimization methods proposed have been demonstrated on 12-bus, 34-bus, and 69-bus radial distribution system consisting of 11, 33, and 68 sections, respectively. MATLAB, Version 7.10 software is used for simulation.

1. Introduction

As a qualified field, evolutionary computation is somewhat young and it was invented very lately in 1991. It represents an attempt to bring jointly researchers, who have been following special approaches to simulate various aspects of evolution. The techniques Genetic Algorithms, evolution strategies, and evolutionary programming have reproduction, random variation, competition, and selection of challenging individuals in a population. The first glimpses of ideas of Genetic Algorithms (GAs) are found in Holland's papers in the early 1960s. Since 1960s, in the optimization world, Genetic Algorithm (GA) is playing a leading role and it has proved its supremacy in number of occasions for resolving the complex problems. Strengths of a real-coded GA are

- Increased efficiency (no need to convert bit strings)
- Increased precision (using real numbers)
- Can use different mutation and crossover techniques

But it has limitations like,
- Getting trapped in local minima.
- Three step procedures such as selection, crossover and mutation that increase computational time.

It enforced the researchers to look for well-organized optimization techniques. In the early 1995, when Kennedy and Eberhart (Singh & Rao, 2012) proposed Particle Swarm Optimization (PSO), it shifted the optimization world towards social behavior inspired algorithms. PSO is popular for faster convergence. It is also effectively implemented for solving the complex problems. Particle Swarm Optimization (PSO), Hybrid Particle swarm Optimization, (HPSO) and Multi-Agent Particle Swarm Optimization (MAPSO) are among the popular meta-heuristic methods in all the engineering fields (Kannan, Renuga, Kalyani, & Muthukumaran, 2011).

Bacterial Foraging Optimization (BFO) algorithm was invented by Passino in the near beginning of 2002. BFO algorithm attempts to mock-up the individual and group behavior of *E. Coli* bacteria as a scattered optimization process. One key step in BFO algorithm is the computational chemo taxis, where a bacterium (which models a candidate solution of the optimization problem) takes steps over the foraging site in order to attain the area with high-nutrient content (corresponding to higher fitness) (Das, Dasgupta, Biswas, Abraham, & Konar, 2009).

But the complexity of BFO algorithm forced researchers to find a simple way for faster convergence (Gollapudi, Pattnaik, Bajpaib, Devi, & Bakwad, 2011). In this paper it is proved that the convergence of BFO algorithm is improved using Modified Bacterial Foraging Optimization (MBFO) algorithm. This MBFO algorithm is tested in the optimal placement of Distributed Generation in radial distribution systems.

Distributed Generation (DG) sources are predicated to play major role in distribution systems due to the demand growth for electrical energy. Optimum placement of DG minimizes the line loss; also it improves the voltage stability (Injeti & Prema Kumar, 2013). Various methods including the following were proposed for DG placement and sizing. The analytical approaches (Acharya,

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Mahat, & Mithulananthan, 2006; Wang & Nehrir, 2004) and the novel method (Padma Lalitha, Veera Reddy, Sivarami Reddy, & Usha Reddy, 2011) proposed earlier have complex mathematical calculations. Sensitivity approaches for optimal sizing and placement of DG are discussed exclusively in de Souza et al. (2013) and Murthy and Kumar (2013). Additionally in Aman, Jasmona, Mokhlis, and Bakar (2012), a new algorithm for DG placement and sizing for distribution systems is developed considering the stable node voltages referred as power stability index (PSI).

Biswas, Kumar Goswami, and Chatterjee (2012) proposed a traditionally popular stochastic optimization algorithm, the Genetic Algorithm (GA) to find the optimum placement of DG with minimum line losses and reduction in the voltage sag. A technique for selection of buses based on incremental voltage sensitivities for location of DG has been described in Arya, AtulKoshti, and Choube (2012). It uses Differential Evolution (DE) to evaluate the optimum DG capacity by minimizing transmission losses. Dynamic programming can also be used to determine the optimal location to place DGs in distribution system to minimize power loss of the system and enhance reliability improvement and voltage profile (Khalesi, Rezaei, & Haghifam, 2011). A combination of GA and PSO (Moradi & Abedini, 2012) is used for optimal DG location and sizing in distribution systems to minimize network power losses, with better voltage regulation and to improve the voltage stability.

Recently BFO technique is becoming popular and it has been successfully applied in unit commitment (Eslamian, Hosseinian, & Vahidi, 2009) and optimal capacitor allocation (Tabatabaei & Vahidi, 2011) problems. Combination of PSO and BFO (Saber, 2012) is used for dynamic economic dispatch problem. Also BFO have been used for network reconfiguration with the objective of loss minimization (Sathish Kumar & Jayabarathi, 2012). Even though BFO covers up a broad search area, it is supposed to have a low convergence speed (Mohkami, Hooshmand, & Khodabakhshian, 2011).

In this paper, a Modified Bacterial Foraging Optimization (MBFO) algorithm is proposed to improve the convergence characteristics of BFO algorithm and it is tested in the placement of radial distribution systems to reduce the total loss and to improve the voltage profile. Recently, researchers found that among swarm optimization methods, Bacterial Foraging and Particle Swarm Optimization techniques are very promising and is being used to find the optimal placement and sizing of radial distribution systems recently.

This work shows the fast convergence of BFO algorithm, thereby the drawback of BFO algorithm is eliminated. The performance of the BFO algorithm is improved using this MBFO algorithm and the effectiveness of this work is illustrated using DG placement in radial distribution systems (12-bus, 34-bus, and 69-bus). The accuracy of the test results are compared with the analytical method results and BFO.

2. Basic concepts

2.1. Bacterial Foraging Optimization (BFO)

A group of bacteria move in search of food and away from noxious elements. It is a biological method known as foraging (Passino, 2002). All bacteria try to move towards the food concentration gradient individually. At the initial location, they measure the food concentration, tumble to take a random direction, swim for a fixed distance and measure the concentration there. This tumble and swim make one chemo taxis step. If the concentration is greater at next location, they take another step in that direction. When concentration at next location is lesser than that of previous location, they tumble to find another direction and swim in this new direction. This process is carried out to a certain number of steps, which is limited by the lifetime of the bacteria. At the end of its lifetime, the bacteria that has gathered good health and in better concentration region divides into two cells. Thus in the next reproductive step, the next generation of bacteria starts from a healthy position. The better half reproduces to produce the next generation, whereas the worst half dies. This reproduction step is carried out for a fixed number of times. If the specifications such as number of reproductive steps, number of chemo tactic steps which are consisting of run (or swim) and tumble, swim length, maximum allowable swims in a particular direction are given for a particular problem, the variable can be optimized using this Bacteria Foraging Optimization technique. The *Escherichia Coli* (*E. coli*) bacteria that are present in our intestines have a foraging strategy governed by four processes, namely, chemo taxis, swarming, reproduction, elimination and dispersal (Dasgupta, Das, & Abraham, 2009). The complete structure of this algorithm is shown in Fig. 1.

2.1.1. Chemo taxis

In the presence of chemical attractants and repellents, the bacteria will create the movement patterns. This is called as chemo taxis. This progression was simulated in two special moving ways for *E. coli* bacterium. They are run or tumble. In its whole life, the bacterium swaps between these two processes. Occasionally, the bacterium tumbles after a tumble or after a run. This wavering between the two processes will move the bacterium. This makes the bacterium to search for nutrients. The location of each element in the population of S bacterial at the jth chemo tactic step, and kth reproduction step, and lth elimination is represented as $\theta_i(j,k,l)$. The movement of bacterium may be presented by:

$$\theta_i(j,k,l) = \theta_i(j,k,l) + [C(i)^{*}\phi(j)] \tag{1}$$

where $C(i)$ $(i = 1,2,\ldots,S)$ is the size of the step taken in the random direction specified by the tumble. $\phi(j)$ is used to describe the random direction of movement after a tumble. $J(i,j,k,l)$ is the fitness, and it denotes the cost at the position of the ith bacterium $\theta_i(j,k,l) \in Rn$. If at $\theta_i(j,k,l)$, the cost $J(i,j+1,k,l)$ is better than at $\theta_i(j,k,l)$, then another step size $C(i)$ in this same direction will be taken. Otherwise, bacteria will tumble by means of taking another step of size $C(i)$ in random direction $\phi(j)$, in order to search for better nutrient environment.

2.1.2. Swarming

When a set of *E. coli* cells is placed in the middle of a semisolid agar with single nutrient chemo-effectors, they move away from the middle in a traveling loop of cells by moving up the nutrient gradient produced by utilization of the nutrient by the set. To reach this, reproduce the cell-to-cell signaling through an attractant and a repellant. The mathematical representation for *E. coli* swarming can be represented by:

$$\begin{aligned} Jcc(\theta, P(j,k,l)) = {} & \sum_{i=1}^{S} Jcc(\theta, \theta^i(j,k,l)) \\ & - \sum_{i=1}^{S}\left[-d_{\text{attractant}} \exp\left(-\omega_{\text{attractant}} \sum_{m=1}^{p} (\theta_m - \theta_m^i)^2\right)\right] \\ & + \sum_{i=1}^{S}\left[-h_{\text{repellent}} \exp\left(-\omega_{\text{repellent}} \sum_{m=1}^{p} (\theta_m - \theta_m^i)^2\right)\right] \end{aligned} \tag{2}$$

Now the cost function value is to be added to the actual cost function. S is the total number of bacteria and p is the number of parameters to be optimized which are present in each bacterium. $h_{\text{repellant}}$ is the height of the repellant effect, $w_{\text{repellant}}$ is the width of the