Electrical Power and Energy Systems 83 (2016) 443–449

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Application of hyper-spherical search algorithm for optimal coordination of overcurrent relays considering different relay characteristics

S.A. Ahmadi [a], H. Karami [b], M.J. Sanjari [b,*], H. Tarimoradi [b], G.B. Gharehpetian [b]

[a] *Electrical Engineering Department, Shahid Rajaee Teacher Training University, Tehran, Iran*
[b] *Electrical Engineering Department, Amirkabir University of Technology, Tehran, Iran*

ARTICLE INFO

Article history:
Received 7 April 2015
Received in revised form 12 April 2016
Accepted 12 April 2016
Available online 29 April 2016

Keywords:
Power system protection
Overcurrent relays coordination
Relays characteristics
HSS algorithm

ABSTRACT

Minimization of the discrimination time between the backup and main overcurrent relays is one of the most important issues in the relays coordination of a power system. Finding the Time Setting Multipliers (TSMs) by the evolutionary algorithm has been investigated in the previous papers. In this paper, in addition to TSM, different characteristics of the overcurrent relays are considered to improve coordination. On the other hand, the coordination problem can be considered as an optimization problem, which can be solved by artificial intelligent methods. Recently, a novel optimization algorithm, Hyper-Sphere Search (HSS) algorithm, has been introduced. The HSS algorithm is adapted to the problem of this paper, in order to select the characteristics of the overcurrent relays and their TSMs. The result of HSS is compared with the genetic algorithm which is used in the previous studies. The simulation results on the sample network show the effectiveness of HSS and relays characteristics in terms of better coordination.

Introduction

The main objective in the protection of the power system is to detect and isolate the faulty parts as fast as possible. In distribution systems, overcurrent relays are used for fault clearing. In order to have a reliable protection, a common way is to use a backup relay in addition to the main relay [1,2]. In this protection scheme, the aim is to remove the faulty line quickly by means of the main relay; but if the main relay does not operate after a specific time, the backup relay should operate. In this method, the backup relay should not operate before the main relay; the Coordination time interval (*CTI*) should be considered in the relay operating time [3–5] and the discrimination time between the backup and main relays should be less than *CTI*.

Nowadays, considering the complexity of interconnected power systems, the optimization techniques have been adapted to the problem of relay coordination and selecting optimal relay settings. In [6–8], the optimal coordination of the overcurrent relays has been performed using linear programming approaches, i.e. simplex, dual simplex, and two phase simplex methods. The linear programming methods are highly dependent on the initial values and are very susceptible of trapping in the local minima. In [9], the coordination of the overcurrent relays has been optimized by evolutionary algorithms. Genetic Algorithm (GA) is one of the first evolutionary algorithms that have been used to solve the coordination problem. In [10,11], the relays have been tuned by a GA-based method. Another evolutionary algorithm which has been used in relay coordination problem is particle swarm optimization (PSO). In [12], the protection coordination has been done by the PSO method.

In all the aforementioned papers, the characteristics of the overcurrent relays have been considered to be fixed during the optimization procedure, and only the TSM of the relays have been selected. In this paper, the characteristics and TSM of the overcurrent relays are selected and the protection coordination problem will be solved. Different optimization algorithms have been adapted from many papers in order to solve electrical engineering problems [13–16]. Despite the effectiveness of the evolutionary algorithms, they sometimes converge to the poor local minima; therefore, it is important to use a more powerful and trusty optimization algorithm. There are many optimization algorithms that are used in the engineering problems. In [17,18], the Harmony Search Algorithm (HSA) has been used to optimize scheduling of a home energy system. In [19], the Colonial Competitive Algorithm (CCA) has been applied to investigate effect of battery efficiency on the energy management of a system. In [20], an effective optimal method is presented to control the distributed energy resources in a microgrid to guarantee its stability after islanding occurrence considering voltage and frequency deviations. In this paper, a novel

* Corresponding author.
E-mail address: m_j_sanjari@aut.ac.ir (M.J. Sanjari).

http://dx.doi.org/10.1016/j.ijepes.2016.04.042
0142-0615/

optimization algorithm, Hyper-Sphere Search (HSS) algorithm [21], is adapted to relays coordination problems by adding a new discrete part to the continuous HSS which enables us to select the relay characteristics to improve the protection coordination. In [21], HSS has been compared with GA, PSO and HSA using mathematic problems and in [22], HSS has been compared with HSA and CCA for optimal scheduling of a smart energy system. The proposed method is simulated on a sample network and it is shown that the discrete–continuous Hyper-Sphere Search (DC-HSS) algorithm is an effective tool for the optimization of protection coordination problems. In order to show the privilege of the DC-HSS, the results are compared with the GA.

In the next section, the objective function (OF) used in this paper is introduced. The proposed algorithm is presented in Section 'DC-HSS algorithm'. Then in Section 'Test results', the optimal coordination is performed for a test system and the TSMs and characteristics of the overcurrent relays are optimally selected.

Relays coordination objective function

As mentioned before, in order to have a reliable protection, the backup relay should not operate before the main relay. Therefore, the coordination constrain is as follows:

$$t_{bOC} - t_{mOC} \geqslant CTI \tag{1}$$

where t_{bOC} and t_{mOC} are the backup and main overcurrent relays operating times, respectively and *CTI* is the coordination time interval. In optimization methods, the above constraint is combined with the objective function (*OF*). The coordination *OF*, used in this paper, is introduced in [11] as follows:

$$OF = \alpha_1 \sum (t_i)^2 + \alpha_2 \sum (\Delta t_{mb} - \beta(\Delta t_{mb} - |\Delta t_{mb}|))^2 \tag{2}$$

$$\Delta t_{mb} = t_b - t_m - CTI \tag{3}$$

where t_i is the operating time of the *i*-th overcurrent relay and Δt_{mb} is the discrimination time between backup and main relays for the fault that occurs just close to the circuit breaker α_1, α_2 and β are the weighting factors.

The operating time of overcurrent relays can be calculated by the following equation:

$$t = TSM\left(\frac{K}{M^{\alpha} - 1} + L\right) \tag{4}$$

where K, α and L depend on the relay characteristics that are given in Table 1, and M is the ratio of the short circuit current (I_{SC}) to the pickup current (I_{pickup})of the overcurrent relay.

$$M = \frac{I_{sc}}{I_{pickup}} \tag{5}$$

In the next section, the DC-HSS algorithm is introduced. The DC-HSS selects TSMs in the range of 0.05–2 and the relay characteristics by choosing the best M, α and L from Table 1.

DC-HSS algorithm

Continuous HSS

From a general point of view, the optimization is a process in order to make something better, which is modeled as follows:

$$\min\{f(x)|x\epsilon X\} \tag{6}$$

subject to: $g(x) \geqslant 0$ and $h(x) = 0$.

It is expected to minimize $f(x)$ through the optimization procedure. All the problems in the real world are exposed to some constraints categorized as equality and inequality constraints, $h(x)$ and $g(x)$, respectively. The value of $f(x)$ depends on the set of decision variables, x which have the possible range of values such that $X_{i,\min} \leqslant x_i \leqslant X_{i,\max}$.

The HSS algorithm procedure is divided into four steps as follows:

Step 1: Particles initialization

This step initializes the HSS algorithm and includes four substeps as follows:

(a) *Initialization of parameters:* Some parameters of this algorithm should be assigned by the user and these are N_{pop} (number of initial population), N_{SC} (number of hyper-sphere centers), $r_{\min}$, $r_{\max}$, Pr_{angle} and N_{newpar} that will be defined in the following sections.
(b) *Initial population generation:* The HSS algorithm starts with N_{pop} randomly generated solutions which are randomly selected from $[X_{i,\min}, X_{i,\max}]$ with a uniform probability. For each solution, which is called particle, the objective function is calculated.
(c) *Hyper-sphere center nomination:* The particles are sorted based on their calculated objective function values in ascending order and the best N_{SC} particles are selected to be the hyper-sphere centers (SCs). In an N-dimensional optimization problem, a particle is indicated by a $1 \times N$ vector, $[p_1, p_2, \ldots, p_N]$ in which p_i are the decision variables for $i = 1, \ldots, N$ and $f(p_1, p_2, \ldots, p_N)$ is the objective function value of a particle.
(d) *Particles distribution among hyper-spheres:* The N_{SC} of the population are selected as SCs. The remaining particles are distributed among SCs considering the SCs dominance, which is inversely proportional to their values for the objective function. The Objective Function Difference (*OFD*) for each SC is defined to divide the particles proportionally as $OFD_{SC} = f_{SC} - \max_{SCs}\{f\}$. Therefore, the normalized dominance of each SC is defined by the following equation:

$$D_{SC} = \left|\frac{OFD_{SC}}{\sum_{i=1}^{N_{SC}} OFD_i}\right| \tag{7}$$

Table 1
Characteristic of overcurrent relays.

Number of characteristic	Type of characteristic	Standard	K factor	α factor	L factor
1	Short time inverse	AREVA	0.05	0.04	0
2	Standard inverse	IEC	0.14	0.02	0
3	Very inverse	IEC	13.5	1	0
4	Extremely inverse	IEC	80	2	0
5	Long time inverse	AREVA	120	1	0
6	Moderately inverse	ANSI/IEEE	0.0515	0.02	0.114
7	Very inverse	ANSI/IEEE	19.61	2	0.491
8	Extremely inverse	ANSI/IEEE	28.2	2	0.1217