Research Journal of Applied Sciences, Engineering and Technology 13(8): 626-631, 2016
DOI:10.19026/rjaset.13.3048
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: June 12, 2015 Accepted: July 8, 2015 Published: October 15, 2016

Research Article

Optimal DG Allocation in Distribution Networks using Cat Swarm Optimization

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Abstract: Dispersed or Distributed Generations (DGs) are becoming more popular on account of socio-economic reasons and also to enhance performance of distribution systems. Cat Swarm Optimization (CSO) is one of the recent swarm-intelligence-based optimization techniques which provides local and global search simultaneously. The aim of this study is to introduce the application of CSO method for optimal allocation of DGs in distribution networks. The problem is formulated to maximize annual energy loss reduction and to maintain a better node voltage profile under piece-wise multi-level load profile using penalty factor approach. Modification is suggested in CSO to enhance its exploration and exploitation potentials. In addition, clever search is proposed to enhance overall performance of the optimizing tool. The proposed method is applied on the benchmark IEEE 33-bus and 69-bus system and the obtained results are promising.

Keywords: Cat swarm optimization, clever search, distributed generations, radial distribution network, swarm intelligence

INTRODUCTION

Indian smart grid initiatives are an emerging part of the energy policy of central and state governmental entities that focus on capacity increase to meet the growing electricity demand, rural electrification and optimizing electrical usage through load management and improving operational efficiencies (El-Hawary, 2014). To achieve these applications the penetration level of DGs in power system has been increasing during the last few years due to the significant advances in several generation technologies, deregulation of power systems, environmental impacts and construction issues of new transmission lines (Moravej and Akhlaghi, 2013). DG units are typically connected so that they work in parallel with the utility grid and they are placed depending on availability of the resources (Al Abri *et al*., 2013). The advantages associated with DG's depends greatly how optimally they are being placed in distribution networks as inappropriate placement can increase system losses, associated costs and therefore, can have an opposite effect to what is desired.

The optimal DG allocation problem involves the determination of sizing and siting of DGs to meet out desired objectives while satisfying several operational constraints. It is a mixed integer, non-linear, complex combinatorial optimization problem and has been solved efficiently using modern population based techniques such as Particle Swarm Optimization (PSO) (El-Zonkoly, 2011; Abdi and Afshar, 2013; Kayal and Chanda, 2013; Kansal *et al*., 2013), Artificial Bee Colony Algorithm (ABC) (Abu-Mouti and El-Hawary, 2011), Genetic Algorithm (GA) (Celli *et al*., 2005; Shukla *et al*., 2010), Harmony Search Algorithm (HSA) (Kollu *et al*., 2014; Rao *et al*., 2013), Evolutionary Programming (EP) (Khatod *et al*., 2013) and Teaching Learning Based Optimization (TLBO) (Garcia and Mena, 2013), Cuckoo Search Algorithm (CSA) (Moravej and Akhlaghi, 2013), Bacterial Foraging Optimization (BFO) (Mohamed and Kowsalya, 2014) and Tabu Search (TS) (Golshan and Arefifar, 2006), etc. However, each of these techniques has associated with its own inherent disadvantage. The dependency of the PSO algorithm on the adjusting parameters and the possibility of trapping in local optima can reduce the efficiency and accuracy of the algorithm at different situations (Kavousi-Fard and Niknam, 2013). The disadvantage of GAs is the premature convergence to a local optimum; high processing time associated that make the algorithm quite slow (De Souza *et al*., 2004). Simulated Annealing (SA) provides better solution, it requires excessive processing time and makes little use of memory (Golshan and Arefifar, 2006). Moreover, many of these algorithms are not performing global exploration and local exploitation simultaneously and therefore it is difficult to decide the switchover between these two phases of the search process.

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Cat Swarm Optimization (CSO) is a new high performance computational method, inspired from the natural behavior of cats (Pappula and Ghosh, 2014). It was introduced by Chu and Tsai in 2007. Cats have a strong curiosity towards moving objects and possess good hunting skill (Saha *et al*., 2013). The important property of CSO is that it provides local as well as global search capability simultaneously (Pradhan and Panda, 2012). It has been successfully applied to solve diverse engineering optimization problems such as Infinite Impulse Response (IIR) system identification (Panda *et al*., 2011), clustering (Santosa and Ningrum, 2009), synthesis of linear antenna arrays (Pappula and Ghosh, 2014), linear phase Finite Impulse Response (FIR) filter design (Saha *et al*., 2013), etc. However, it has not been yet attempted to solve the optimal DG placement problem.

The optimal DGs allocation problem offers enormous search space and this increases computational burden of these search algorithms. To reduce this search space generally top few top nodes are selected as candidate nodes from the node priority list which is being obtained on the basis of certain sensitivity based approach (Kollu *et al*., 2014; Rao *et al*., 2013; Khatod *et al*., 2013). This approach definitely reduces the computational time of search algorithms, but a large region of search space remains unexplored. This guarantees sub-optimal solution, if any node of the optimal solution is not located in the reduced problem search space so obtained.

In this study, CSO has been employed to solve the optimal DGs allocation problem of distribution systems. The proposed mathematical modeling is designed to maximize annual energy loss reduction while maintaining better system node voltage profile using penalty function approach considering piece-wise multi-level load profile. The optimal dispatches of DGs are determined at each load level separately and then the performance of the distribution network is evaluated. The problem search space offered to effectively scanned by proposing clever search to enhance the convergence, accuracy and efficiency of the optimizing technique. The application results are compared with other swarm and evolutionary based algorithms.

PROBLEM FORMULATION

The optimal placement of DGs in distribution system can significantly reduce annual energy losses in distribution feeders and also improve its node voltage profile. In this work, these two objectives are considered and are combined into a single objective function using a penalty factor approach. The penalty factor is suitably designed to take care in the selection of that DG allocation which provides better voltage profile while maintaining all node voltages within prescribed limits. The system load is stochastic in nature and to deal with this characteristic of the distribution systems, the annual load duration profile of the distribution network is piecewise linearized into definite number of different load levels. The Objective Function (*O.F.*) is therefore formulated as:

$$Maximize\ \ O.F. = \lambda\left[\sum_{j=1}^{N_L}(E_{bj} - E_{cj})\right] \tag{1}$$

$$\lambda = \frac{1}{\left(1 + Max\left(\Delta V_p\right)\right)} \tag{2}$$

where,

$$\Delta V_p = \begin{Bmatrix} 1-\left|V_p\right| & ;V_{\min S} < V_p < V_{\min} \\ 0 & ;V_{\min} \le V_p \le V_{\max} \\ \text{a very large number} & ;\ \text{else} \end{Bmatrix}; \forall p \in N \tag{3}$$

The objective function defined by (1) is maximized subjected to the following system operational constraints (4)-(8).

Power flow equations:

$$g(k) = 0 \tag{4}$$

Feeder current:

$$I_f \le I_{f,rated} \tag{5}$$

Node compensation limit:

$$P_{DG,min} \le P_{DG,p} \le P_{DG,max}; \forall p \in N \tag{6}$$

Total active power demand:

$$\sum P_{DG,p} \le P_D; \forall p \in N \tag{7}$$

Also, it is ensured that no candidate nodes for DG placement are repeated:

$$N_{DG,a} \ne N_{DG,b};\ a,b \in N \tag{8}$$

CAT SWARM OPTIMIZATION

Chu and Tsai have proposed a new optimization algorithm in 2007 which imitates the natural behavior of cats (Panda *et al*., 2011). Cats first move step-by-step very cautiously toward the prey till they realize that it is in their promising reach and then they attack on it with full energy. These two characteristics i.e., move step-by-step and chasing with full energy are represented by seeking and tracing modes, respectively. The seeking mode corresponds to a global search process whereas the tracing mode corresponds to a local search process (Pradhan and Panda, 2012). To combine the two modes into the algorithm, a Mixture Ratio (MR) is defined. In CSO these two modes of operations are mathematically modeled for solving complex optimization problems and can be described by seeking and tracing modes (Panda *et al*., 2011):

Seeking mode: The seeking mode corresponds to a global search technique in the search space of the optimization problem. Some of the terms related to this mode are:

- **Seeking Memory Pool (SMP):** It is the number of copies of a cat produced in seeking mode.
- **Seeking Range of selected Dimension (SRD):** It is the maximum difference between the new and old values in the dimension selected for mutation.
- **Counts of Dimension to Change (CDC):** It is the number of dimensions to be mutated.

The steps involved in this mode are:

- Create SMP copies of the i^{th} cat.
- Based on CDC update the position of each copy by randomly adding or subtracting SRD percent the present position value.
- Evaluate the fitness of all copies
- Pick the best candidate from all copies and place it at the position of the i^{th} cat.

Tracing mode: The tracing mode corresponds to a local search technique for the optimization problem. In this mode, the cat traces the target while spending high energy. The rapid chase of the cat is mathematically modeled as a large change in its position. Define position and velocity of i^{th} cat in the D-dimensional space as $x_i = (x_{i1}, x_{i2},....., x_{iD})$ and $v_i = (v_{i1}, v_{i2}, ..., v_{iD})$ where ($1 \leq d \leq D$) represents the dimension. The global best position of the cat swarm is represented as $P_g = (P_{g1}, P_{g2}, ..., P_{gD})$. The update equations are:

$$v_{i+1,d} = W\, v_{i,d} + C\, r\, (P_{gd} - x_{id}) \tag{9}$$

$$x_{i+1,\, d} = x_{i,d} + v_{i+1,d} \tag{10}$$

where,
W = The inertia weight
C = The acceleration constant
r = A random number uniformly distributed in the range [0, 1].

The algorithm initializes with a predefined population size which is being distributed randomly in the problem search space. However, in order to improve the computational efficiency of the algorithm, clever search is employed as described in the next section. The algorithm terminates when the maximum iteration count is achieved.

Clever search: A new approach is proposed to identify the better nodes for DG placement and then they are selected cleverly while maintaining sufficient diversity in the population. In this approach, a small test DG capacity *dP* is installed subsequently at all nodes of the distribution network and the objective function is evaluated at each instance. The node that provide the maximum function value is found and that small DG capacity *dP* is then placed at this node. After the placement of the *dP*, the next most optimal candidate node is explored in the same manner to place next small DG. This process is repeated till there is an improvement in the fitness. In this way a node priority list is obtained for DG placement. The candidate nodes are selected from this list using Roulette Wheel Selection so that candidate nodes are selected according to their probability of priority. This provides better opportunity to better nodes while keeping poor nodes in the problem search space. Thus, the diversity in population is maintained whereas the population quickly picks up better fitness. This improves the computational efficiency of the CSO.

SIMULATION RESULTS

The proposed method is applied on the benchmark IEEE 33-bus (Baran and Wu, 1989) and 69-bus (Das, 2008) test distribution systems. The initial configuration, nominal line voltage and power demands are given in Table 1 and the detailed system data may be referred from the respective references. The annual load profile is piecewise segmented in three different load levels, i.e., light, nominal and peak which are 50, 100 and 160% of the nominal system loading (Das, 2008). The load durations are taken 2000, 5260 and 1500 hours for light, nominal and peak load respectively. The values of CSO parameters selected for simulation are shown in Table 2. The maximum DG capacity at single node is taken 2 MW and it is assumed that the control settings are available in the steps of 1kW. The maximum candidate sites for DG allocation is taken as 3. The proposed algorithm has been developed using MATLAB and the simulations have been carried on a personal computer of Intel i5, 3.2 GHz and 4 GB RAM. After usual tradeoff a population size of 10 and maximum iterations of 100 is set for both test systems.

Case study 1: 33-bus system: The best allocation of DGs obtained after 100 trials and is presented in Table 3. The table shows optimal DG capacities as well as their optimal locations obtained using CSO and are

Table 1: Initial configuration, nominal line voltage and power demand

Particulars	Case study 1	Case study 2
Sectionalizing switches	1-32	1-68
Tie-switches	33-37	69-73
Base configuration (open lines)	33-37	69-73
Line voltage (kV)	12.66	12.66
Nominal active demand (kW)	3715	3802.19
Nominal reactive demand (kVAr)	2300	2694.6

Table 2: Selected CSO parameters

Parameter	Value	Parameter	Value
Population size	10	*SRD*	2
Maximum iterations	100	*MR*	0.1
SMP	5	*W*	0.4
CDC	0.6	*C*	1.5

compared with the recently proposed Harmony Search Algorithm (HSA) of Rao *et al*. (2013) under identical system and design parameters. A comparison of network performance after optimal DG placement is presented in Table 4.

The table shows that there is a marked improvement in power loss reduction and voltage profile improvement using optimal DG placement. The table also compares the results obtained using CSO with HSA (Rao *et al*., 2013) under identical system and design parameters. The table shows better performance of the proposed method than HSA at each load level. It can also be depicted from the table that using proposed method, the annual energy losses are 9.21% less than (Rao *et al*., 2013).

Case study 2: 69-bus system: This is one of the most popular systems available in literature. The best allocation of DGs obtained after 100 trials of CSO is presented and compared with HSA (Rao *et al*., 2013) in Table 5. A comparison results after optimal DG placement using CSO with HSA (Rao *et al*., 2013) is shown in Table 6. The table shows that CSO also performs better than HSA for this test system also. This is true for each load level. The table also shows that using CSO, the annual energy losses are 4.49% less than HSA (Rao *et al*., 2013).

DISCUSSION

It is noteworthy that the optimal siting and sizing obtained using CSO is entirely different than that obtained by HSA (Rao *et al*., 2013) and the results obtained using CSO are better. This is true for both case studies. Therefore, the proposed method has intensive potential to efficiently solve hard combinatorial optimization problems.

The computational performance of any population based search technique can be judged after observing its solution quality of a sample of solutions obtained after a definite number of independent trials. The quality of solutions obtained after 100 trails of CSO for both case

Table 3: Optimal DG allocation for case study 1

	Optimal DG Capacity in MW (Optimal Location)	
Load level	HSA (Rao *et al*., 2013)	CSO
Light	0.1777(17), 0.1303(18), 0.5029(33)	0.376(14), 0.537(24), 0.529(30)
Nominal	0.5724(17), 0.1070(18), 1.0462(33)	0.756(14), 1.095(24), 1.065(30)
Peak	0.9108(17), 0.1939(18), 1.6115(33)	1.117(14), 1.200(24), 1.633(30)

Table 4: Comparison results for case study 1

Load Level	Particulars	Base case	HSA (Rao *et al*., 2013)	CSO
Light	Power loss (kW)	47.06	23.29	17.330
	Minimum voltage (p.u.)	0.9583	0.9831	0.9845
Nominal	Power loss (kW)	202.67	96.76	71.450
	Minimum voltage (p.u.)	0.9131	0.9670	0.9685
Peak	Power loss (kW)	575.27	260.97	196.65
	Minimum voltage (p.u.)	0.8529	0.9437	0.9420
Annual energy loss reduction (%)		-	53.17	65.120

Table 5: Optimal DG allocation for case study 2

	Optimal DG capacity in MW (optimal location)	
Load level	HSA (Rao *et al*., 2013)	CSO
Light	0.5857(63), 0.1280(64), 0.2579(65)	0.258 (17), 0.716 (61), 0.150 (64)
Nominal	1.3024(63), 0.3690(64, 0.1018(65))	0.545(17), 1.440(61), 0.329(64)
Peak	1.9710(63), 0.8308(64), 0.1589(65)	0.869(17), 2.000(61), 0.837(64)

Table 6: Comparison results for case study 2

Load level	Particulars	Base case	HSA (Rao *et al*., 2013)	CSO
Light	Power loss (kW)	51.61	21.92	17.44
	Minimum voltage (p.u.)	0.9567	0.9846	0.9898
Nominal	Power loss (kW)	225.00	86.77	71.14
	Minimum voltage(p.u.)	0.9092	0.9677	0.9806
Peak	Power loss (kW)	652.53	230.61	187.67
	Minimum voltage (p.u.)	0.8445	0.9478	0.9693
Annual energy loss reduction (%)		-	62.64	69.51

Table 7: Solution quality of CSO

Particulars	Case study 1	Case study 2
Best fitness	1105343.97	1341317.96
Mean fitness	1100977.61	1336221.74
Worst fitness	1055430.05	1316049.41
SD	10690.4600	5004.20000
COV	0.97000000	0.37000000
EFB	1.04000000	0.53000000
CPU time (s)	118.860000	373.980000

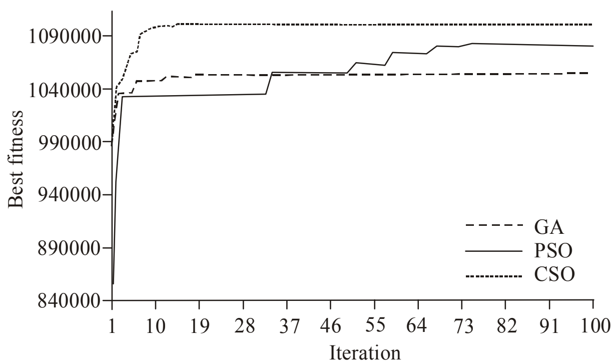

Fig. 1: Convergence characteristics of GA, PSO and CSO for case study 1

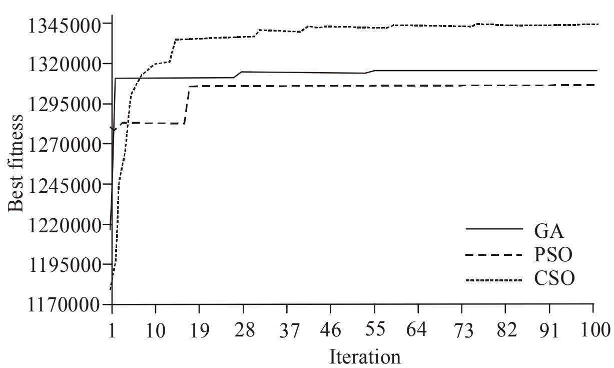

Fig. 2: Convergence characteristics of GA, PSO and CSO for case study 2

studies is presented in Table 7. It can be observed from the table that the best, mean and worst fitness of the 100 sampled solutions are in close proximity. The table also shows the Standard Deviation (SD), Coefficient of Variation (COV) and Error From the Best (EFB) for these sampled solutions. The COV and EFB are within permissible range and it shows that the central tendency of these solutions is quite narrow. The table also shows the average CPU time which is reasonable as it is the problem of planning horizon. Thus, the proposed method is capable to consistently generate solutions of good quality.

In order to compare the convergence behavior of CSO with well-known metaheuristics techniques like GA and PSO, these algorithms are also applied to both test systems. The convergence characteristics of these algorithms are compared in Fig. 1 and 2. A common conclusion can be drawn from these figures that GA converges to suboptimal solution due to lack of exploitation potential. PSO is exploiting the search space in much better way than GA, but it usually trapped in local optima. However, CSO has shown better convergence than GA and PSO on account of simultaneous local and global search. In CSO, the individuals reach the promising region in the initial phase. This happens due to the combined effect of seeking and tracing mode that provides simultaneous exploration and exploitation of the search space. Thus CSO is capable to explore that potential solution which provides better savings in annual energy losses than other recently established technique.

CONCLUSION

The optimal allocation of DGs in distribution networks is now becoming important owing to economic as well as environmental reasons and also to enhance the level of network performance and customers' satisfaction. This study addresses the optimal allocation of dispatchable DGs in distribution systems using a powerful swarm intelligence-based optimization technique, Cat Swarm Optimization (CSO). The proposed formulation for DG allocation effectively minimizes the annual energy losses while providing better node voltage profiles. The proposed clever search causes virtual squeezing of the search space though it maintains a requisite amount of diversity. This improves accuracy and convergence of the algorithm and that is at reduced computational burden. CSO has shown special feature that it provides local as well as global search simultaneously. All these lead to good solution quality. The application results show that there is a significant improvement in the desired objectives. The application results are also found to be better than other established swarm and evolutionary based techniques.

NOMENCLATURE

E_{bj}	:	Energy loss for uncompensated system at *j*th load level
E_{cj}	:	Energy loss for compensated system at *j*th load level
N_L	:	Total number of load levels
$V_{\max}$	:	Maximum node voltage (p.u.)
$V_{\min}$	:	Minimum node voltage (p.u.)
ΔV_p	:	Maximum node voltage deviation at *p*th node (p.u.)
V_{minS}	:	Minimum specified node voltage (p.u.)
V_p	:	Voltage at *p*th node (p.u.)
I_f	:	Feeder current (p.u.)
$I_{f,rated}$	:	Rated feeder current (p.u.)
$P_{DG,min}$	:	Minimum active compensation provided by DGs (kW)
$P_{DG,max}$	:	Maximum active compensation provided by DGs (kW)
P_D	:	Nominal active power demand of the system

P_{DG} : Maximum DG capacity at one candidate node
N_{DG} : Candidate nodes for DG placement
N : Set of system nodes
λ : Node voltage deviation penalty factor

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