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MULTI-OBJECTIVE OPTIMAL DG ALLOCATION IN DISTRIBUTION NETWORKS USING BAT ALGORITHM

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ABSTRACT

The Distributed Generations (DGs) storage may store energy during solar energy peak and use it during peak demand. Proper allocation of DG storage is essential to extract maximum possible benefits. This paper introduces a Bat Algorithm (BA) for optimal allocation of DGs in radial distribution networks. The problem is formulated to maximize annual energy loss reduction and to maintain a better node voltage profile under a piece-wise linear variable load pattern using a penalty factor approach. The proposed method is applied on the benchmark IEEE 33-bus and 69-bus system available in literature and the results obtained are promising.

INTRODUCTION

The growth of electrical energy demand requires more power transfer capacity of distribution networks, but the construction of new distribution lines facilities are constrained by environmental concerns and increasing costs. Distributed generation (DG) systems provide new alternatives to expand the distribution network capacity of existing distribution lines [1]. Also deregulating electric power networks is one of the factors that hasten DG unit applications [2]. DGs are not centrally planned nor centrally dispatched and usually connected to the distribution network in the range say, 100 kW-100 MW. Although DGs are of small size they can affect performance of distribution systems to good margins in different sense as voltage and reliability enhancement, network upgrade deferral, loss reduction, etc. When DGs are installed for loss reduction, there are several challenges associated with the proper location, size and operating strategies, etc. Even if the location is fixed for some reason, improper size would increase the losses in the system beyond the losses for the case without DG [3]. So, the advantages associated with DG's depend greatly on how optimally they are being placed in distribution networks.

For optimal DG allocation, different techniques are used such as analytical, heuristic, meta-heuristic, etc. As DG placement problem is a mixed integer, non-linear, highly complex combinatorial optimization problem where certain operational and network constraints are to be satisfied, so modern meta-heuristic methods have more potential to solve this problem. Different meta-heuristic techniques used in literature are ABC [2], GA [4], PSO [5, 6], HSA [7, 8], EP [9] and TLBO [10], etc. BA is one of the recently developed nature-inspired algorithms proposed by Xin-She Yang in 2011. BA is a numerical optimization approach that is simple, easy to implement, significantly faster than other algorithms, and robust [11]. BA has not been applied to solve the optimal DG placement problem.

The optimal DGs allocation problem offers enormous search space and this increases the computational burden of search algorithms. To reduce the search space generally only a 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 [7-9, 12, 13]. This approach definitely reduces the computation time of search algorithms, but a large area of search space remains unexplored. This guarantees a suboptimal solution, if the node of the global solution is not considered as one of the candidate nodes.

In this paper, BA has been applied for the first time to solve the optimal DGs allocation problem of distribution systems. The proposed mathematical modeling suggests maximization of annual energy loss reduction and improvement of system node voltage profile using a penalty function approach while considering variable piece-wise linear load pattern. The optimal settings of DGs are determined at each load level separately and then the power loss and minimum node voltages are obtained for the respective load levels. The problem search space is effectively scanned by proposing a heuristic based sensitivity approach to enhance the performance of the BA. The performance of the BA is compared with other established population based algorithms.

NOMENCLATURE

A_i	Pulse loudness
E_{bi}	Energy loss for uncompensated system at i^{th} load level (kWh)
E_{ci}	Energy loss for compensated system at i^{th} load level (kWh)
f_i	Pulse frequency of the *i*th bat
$f_{i,d}$	Pulse frequency of the *i*th bat for dth dimension
f_{max}/ f_{min}	Maximum/ minimum pulse frequency
I_f	Feeder current (p.u.)
$I_{f,rated}$	Rated feeder current (p.u.)
N_{DG}	Candidate nodes for DG placement
N	Total number of system nodes
N_L	Total number of load levels
P_D	Maximum candidate DG capacities at all candidate locations (kW)
P_{DG}	Maximum candidate DG capacities at one candidate node (kW)
$P_{DG,min}$	Minimum active compensation provided by DGs (kW)
$P_{DG,max}$	Maximum active compensation provided by DGs (kW)
r_i	Emission pulse rate
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.)
v_i	Velocity of the *i*th bat
x^*	Position of the current best bat
x_i	Position of the *i*th bat
λ	Node voltage deviation penalty factor

PROBLEM FORMULATION

The optimal placement of DGs in distribution system can significantly reduce annual energy losses occurred 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 is therefore formulated as:

Maximize,

$$O.F = \lambda\left[\sum_{i=1}^{N_L}(E_{bi} - E_{ci})\right] \tag{1}$$

$$\lambda = 1/(1+ (Max\ (\Delta V_p))) \tag{2}$$

where,

$$\Delta V_p = \begin{cases} 1 - \mid V_p \mid & ; V_{min}<V_p<V_{minS} \\ 0 & ; V_{max} \geq V_p \geq V_{minS} \\ \text{a very large number} & ; \text{else} \end{cases} \tag{3}$$

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

1. Power flow equations

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

2. Feeder current limits

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

3. DG limits

$$P_{DG,min} \leq P_{DG} \leq P_{DG,max} \tag{6}$$

4. Total DG penetration limit

$$P_{DG} \leq P_D \tag{7}$$

Also it should be ensured that no candidate nodes for DG placement are repeated.

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

BAT ALGORITHM

The bat algorithm is a new swarm intelligence optimization method inspired by the social behaviour of bats and the phenomenon of echolocation to sense distance [14]. Bats are fascinating animals. They have advanced capability of echolocation [15]. It implements the same dynamics of a particle swarm optimization algorithm (PSOA), but the loudness and pulse rate make the BA works like the standard PSO combined with an intensive local search which is very similar to some simulated annealing method for local search [14]. It has two phases, namely, random fly and local random walk. The participation in either of these two phases is decided by its parameters, i.e., loudness and the pulse rate, both are varying with iteration but in opposite fashion. As a result, the promising region is quickly determined and then its extensive local exploitation is provided by the best individual. As the best individual updates the other individuals follows it and thus obtains global or near global solution. The mathematical modeling of BA can be described as below [15].

In BA, each bat is defined by its position $x_i(t)$,velocity $v_i(t)$, frequency f_i, loudness $A_i(t)$, and the emission pulse rate r_i(t) in a *d*-dimensional search space. The new solutions $x_i(t)$ and velocities $v_i(t)$ at time step t are given by

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \tag{9}$$

$$v_i(t) = v_i(t-1) + (x_i\ (t) - x^*)f_i \tag{10}$$

$$x_i(t) = x_i\ (t-1) + v_i(t) \tag{11}$$

Where, β is a random vector in the range [0, 1] drawn from a uniform distribution and x^* is the current global best location (individual). For the local search part, once a solution is selected among the current best individuals, a new solution for each bat is generated locally using random walk by

$$x_{new} = x_{old} + \varepsilon\langle A(t)\rangle \tag{12}$$

Where, ε is a scaling factor which is a random number in the range [–1, 1], while $\langle A(t)\rangle$ is the average loudness of all the bats at time step t. The loudness A_i and the pulse rate r_i of each bat is updated at each iteration using following equations:

$$A_i(t+1) = \alpha\ A_i(t) \tag{13}$$

$$r_i(t+1) = r_i(0)[1 - \exp(-\gamma t)] \tag{14}$$

where, α and γ are constants.

CLEVER SEARCH

A new approach is proposed to identify the optimal nodes for DG placement that are selected cleverly while maintaining sufficient diversity. In this approach, a small test DG capacity *dP* is installed subsequently at all nodes of the distribution network and the fitness is evaluated at each time. The node having the maximum fitness 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. In this approach, the problem search space is not squeezed but is examined effectively without loss of diversity. This improves the computational efficiency of the BA.

SIMULATION RESULTS

The proposed method is applied on the benchmark IEEE 33-bus [16] and 69-bus [17] 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 [17]. The duration times are taken 2000, 5260 and 1500 hours for light, nominal and peak load respectively. The power losses and minimum node voltage at different load levels are given in Table 2 for the base case system. The maximum DG capacity at single node is taken 2 MW as in [8], and its control settings are available at the interval of 1kW. 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.

Table 1 Initial configuration, nominal line voltage and power demands

Particulars	Case study 1	Case study 2
Base Configuration	33 to 37	69 to 73
Line Voltage	12.66	12.66
Nominal Active Demand (kW)	3715	3802.19
Nominal Reactive Demand (kVAr)	2300	2694.6

Table 2 Power loss and minimum node voltage for base case

Particulars	Case study 1			Case study 2		
	L	N	P	L	N	P
Power loss (kW)	47.06	202.67	575.27	51.61	225.00	652.53
Minimum node voltage (p.u.)	0.9583	0.9131	0.8529	0.9567	0.9092	0.8445

Case Study1: 33-bus System

In this system, the sectionalize switches (normally closed) are numbered from 1 to 32, and the tie-switches (normally open) are numbered from 33 to 37 as shown in Figure 1. The best allocation of DGs obtained after 100 trials and is presented in Table 3. The table shows the DG capacity as well as their optimal locations obtained and are compared with the recently proposed Harmony Search Algorithm (HSA) of [8]. A comparison of results for the optimal solution obtained by [8] and the proposed method is presented in Table 4. The table shows consistently better performance of the proposed method than HSA at each load level. It is also clear from table that using the proposed method, the annual energy losses are 9.21% less than [8] which is quite substantial.

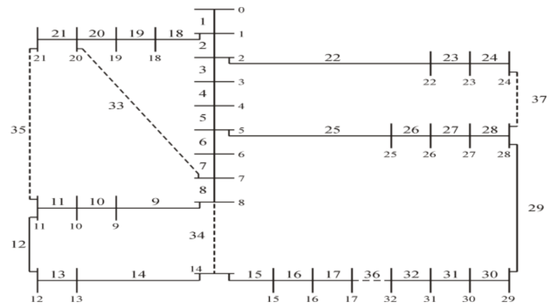

Figure 1 Single line diagram of 33-bus system

Table 3 Optimal DG allocation for Case study 1

Load Level	Optimal DG Capacity in MW (Optimal Location)	
	HSA [8]	BA
Light	0.1303(18)	0.5300(30)
	0.1777(17)	0.5410(24)
	0.5029(33)	0.3740(14)
Nominal	0.1070(18)	1.0680(30)
	0.5724(17)	1.0970(24)
	1.0462(33)	0.7520(14)
Peak	0.1939(18)	1.1580 (30)
	0.9108(17)	1.0970(24)
	1.6115(33)	0.7670(14)

Table 4 Comparison of Results for Case study 1

Load Level	Particulars	HSA [8]	BA
Light	Power Loss (kW)	23.29	17.33
	Minimum Voltage (p.u.)	0.9831	0.9845
Nominal	Power Loss (kW)	96.76	71.45
	Minimum Voltage (p.u.)	0.9670	0.9686
Peak	Power Loss (kW)	260.97	233.61
	Minimum Voltage (p.u.)	0.9437	0.9203
	Annual Energy Loss Reduction (%)	53.17	62.38

Case Study 2: 69-bus System

This distribution system consists of 68 sectionalizing lines and 5 tie lines as shown in Figure 2. The best allocations of DGs obtained after 100 trials of BA is shown in Table 5. Table 6 compares the solutions obtained. A comparison of the results with [8] and the proposed method is presented in table. The table shows better performance of BA than HSA for this system for each load level. The DG installation using the optimal solution obtained by the proposed method improves total annual energy losses reduction by 4.49% in comparison to [8].

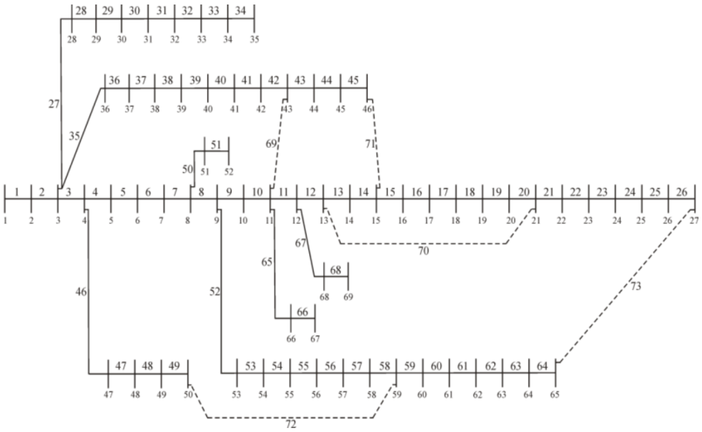

Figure 2 Single line diagram of the 69-bus system

Table 5. Optimal DG Allocation for Case study 2

Load Level	Optimal DG Capacity in MW (Optimal Location)	
	HSA [8]	BA
Light	0.5857(63)	0.2610(11)
	0.1280(64)	0.1860(18)
	0.2579(65)	0.8490(61)
Nominal	1.3024(63)	0.5240(11)
	0.3690(64)	0.3810(18)
	0.1018(65)	1.7220(61)
Peak	1.9710(63)	0.5240 (11)
	0.8308(64)	0.3810(18)
	0.1589(65)	1.8400(61)

Table 6 Comparison Results for Case study 2

Load Level	Particulars	HSA [8]	BA
Light	Power Loss (kW)	21.92	17.04
	Minimum Voltage (p.u.)	0.9846	0.9894
Nominal	Power Loss	86.77	69.42
	Minimum Voltage	0.9677	0.9791
Peak	Power Loss	230.61	230.28
	Minimum Voltage	0.9478	0.9284
Annual Energy Loss Reduction (%)		62.64	67.13

DISCUSSION

The computational performance of any population based search technique can be judged after observing its solution quality which is obtained after a definite number of independent trials. The quality of solutions obtained after 100 trails of BA for both test cases is presented in Table 7. It can be seen from the table that the best, worst and mean of the 100 solutions are in close proximity of each other and also the coefficient of variation (COV) is within permissible range which shows that the central tendency of these solutions is very good.

Table 7 Solution Quality of BA

Particulars	Case study 1	Case study 2
Best Fitness	1105343.97	1341317.96
Mean Fitness	1103341.04	1338785.79
Worst Fitness	1095329.85	1335057.45
COV	0.36	0.20

In order to compare the convergence behavior of BA with GA and PSO, these algorithms are applied to optimize the 33 and 69-bus systems.

The convergence characteristics of these algorithms are compared in Figure 3 and Figure 4. A common conclusion can be drawn from these figures that GA converges to suboptimal solution due to lack of exploitation potential. The PSO is exploiting the search space in much better way than GA, but it trapped in local optima. The BA has shown typical convergence behavior than either GA or PSO. In BA, the individuals find the promising region very quickly and then they exploit it meticulously. That is why it converges to global or near global optima and thus obtain the solution that provides better savings in annual energy losses than other established technique.

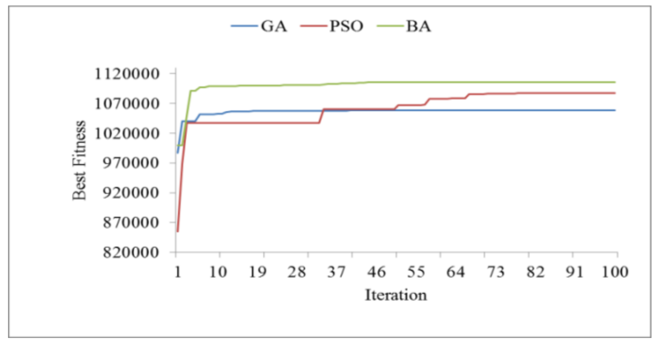

Figure 3 Convergence characteristic of GA, PSO and BA for 33-bus system on multi load levels

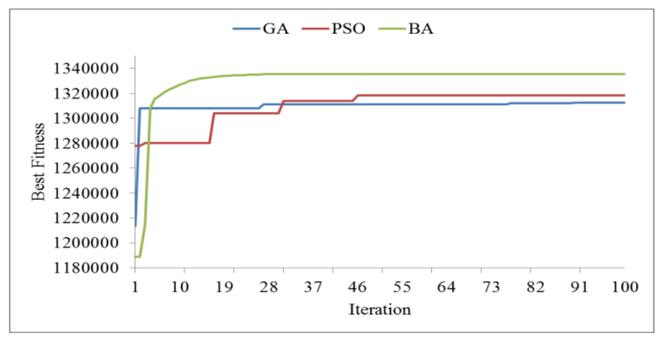

Figure 4 Convergence characteristic of GA, PSO and BA for 69-bus system on multi load levels

CONCLUSIONS

The optimal allocation of DGs in distribution systems is becoming common due to economic, environmental, network performance and customers' satisfaction. This paper addresses the optimal allocation of dispatching DGs in distribution systems using one of the recently developed Bat Algorithm (BA). The key features of this work are: new formulation for DG allocation, clever search of the problem search space and the application of BA to optimize the problem. The annual energy losses and voltage profiles are optimized simultaneously using penalty factor approach. The search space is not reduced but is scanned by proposing a sensitivity based approach. The BA has shown special feature that it identifies the promising region very quickly within few iterations and then it exploit this region meticulously using local random walk around the current best solution. BA has shown better performance than GA, PSO and HSA. The results of the proposed method show that there is a significant improvement in the desired objectives. The proposed method can be extended with other types of DGs operating at non-unity power factors.

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