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MONARCH BUTTERFLY OPTIMIZATION FOR OPTIMAL INTEGRATION OF RENEWABLE ENERGY RESOURCES IN DISTRIBUTION SYSTEMS

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ABSTRACT

In this paper, monarch butterfly optimization is introduced to solve an optimal deployment problem of renewable energy sources in distribution systems, aiming to minimize annual energy loss and node voltage deviation of the system. Solar photovoltaic and wind turbines are considered and formulated for a benchmark 33-bus distribution system. To demonstrate the effectiveness of this technique, obtained simulation results are compared with some of the well-known optimization methods available in literature. The comparison shows that the monarch butterfly optimization has better solution searching ability for real-life engineering optimization problems. Additionally, it provides a higher energy loss reduction.

Keywords: Distributed generation, distribution system, energy loss, monarch butterfly, optimization

1. INTRODUCTION

The Distributed Generation (DG), a concept of accommodating small and medium-sized power generating (especially, renewables) units is one of the sustainable alternatives to conventional large power plants. The increasing risk to the environment and shrinking energy resources have proliferated the growth of renewables in distribution systems. The DGs have numerous technical and environmental advantages if optimally integrated. Some of the benefits of optimal DG integration can include minimization of power loss [1], annual energy loss [2], node voltage deviation, carbon emission [3], and various network reinforcement costs [4]. The problem of distributed energy resources (DER) allocation, considering sites, size, types and numbers, turns out to be a complex mixed-integer, non-linear, and non-convex optimization problem [2]. Therefore, effective optimization methods are required to determine the global optimal solution to maximize DER integration benefits.

In literature, various analytical and meta-heuristic optimization techniques have been suggested and investigated. The analytical methods are computationally fast but produce indicative results, as based on simplified assumptions [5]. Similarly, numerical methods are also computationally fast and efficient but require more accurate problem formulation. On the other hand, population-based meta-heuristic optimization techniques are effective to determine the optimal solution for complex real-life optimization problems. Although, these methods are slow in computation, calculation speed is not a concerning factor in case of DER planning therefore they are mostly preferred.

To solve the DER integration and operation problems, several meta-heuristic optimization methods have been introduced. Some of these can include genetic algorithm (GA) [6], particle swarm optimization (PSO) [7], moth search optimization [8], teaching and learning based optimization (TLBO) [9], water cycle optimization (WCO) [10], etc.

Wang *et al*. [11], introduced a new population-based metaheuristic approach in 2015. The method is inspired from the migration behavior of monarch butterflies found in North America therefore named as monarch butterfly optimization (MBO). The method outperformed some of the existing optimization methods as investigated in [11]. To the best of the authors' knowledge, this method has not been explored to solve complex optimal DER integration problems of distribution systems.

This paper introduces a new optimisation technique to solve optimal DER integration problem of distribution systems, i.e., MBO, aiming to minimize annual energy loss and node voltage deviation of the system. A DER integration problem is formulated considering wind turbines (WTs) and photovoltaics (PVs), and then MBO is applied to solve it. The performance of MBO is found to be promising when compared with some of the well-known optimisation techniques.

2. PROBLEM FORMULATION

In this section, an optimization problem is formulated for optimal integration of multiple WTs & PVs to minimize annual energy loss and node voltage deviation of distribution systems simultaneously. A penalty function based approach is adopted to combine objective functions, expressed as

$$\min F = \varphi \sum_{t=1}^{24} (f_1 \; [1 + f_2]) \tag{1}$$

$$f_1 = \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{r_{ij}\cos(\delta_i - \delta_j)}{V_i V_j} \; (Q_i Q_j + P_i P_j) + \frac{r_{ij}\sin(\delta_i - \delta_j)}{V_i V_j} (Q_i P_j - P_i Q_j) \tag{2}$$

$$f_2 = \max < \Delta V_{i,t} > \quad \forall \; i, t \tag{3}$$

where, $\Delta V_{i,t} =$

$$\begin{cases} |1 - V_{i,t}|, & if \quad V_{\text{minS}} \le V_{i,t} \le V_{\min} \\ 0, & if \quad V_{\min} \le V_{i,t} \le V_{\max} \\ \text{large penalty}, & \text{else} \end{cases} \tag{4}$$

Subject to the following constraints:

$$P_i = V_i \sum_{j=1}^{N} V_{j.} Y_{ij.} \cos(\theta_{ij} + \delta_i - \delta_j) \qquad \forall i \tag{5}$$

$$Q_i = -V_i \sum_{j=1}^{N} V_{j.} Y_{ij.} \sin(\theta_{ij} + \delta_i - \delta_j) \quad \forall \; i \tag{6}$$

$$V_{\min} \le V_i \le V_{\max} \qquad \forall \; i \tag{7}$$

$$0 \le P_i^{\text{der}} \le P_{max}^{der} \qquad \forall \; i \tag{8}$$

$$\sum_{i=1}^{N_{Der}} P_i^{\text{der}} \le 1.6 \sum_{i=1}^{N} P_i^D \tag{9}$$

$$I_{ij} \le I_{ij}^{\max} \qquad \forall \; i \tag{10}$$

here, P_i, Q_i, P_i^{der}, P_i^D, V_i, δ_i are denoting the real and reactive power injections, DER capacity assumed to be deployed, real load demand, voltage magnitude and angle at node *i* respectively. Similarly, I_{ij}, $I_{ij}^{\max}$ and r_{ij} represent current, maximum current limit and resistance of branch connecting nodes *i* and *j*. Furthermore, N, φ, V_{minS}, $V_{\min}$, $V_{\max}$, $P^{\text{der}}_{\max}$ and N_{der} represent the number of buses, daily to annual transformation factor, minimum and maximum specified voltage limits, maximum allowed DER size at a node, and number of DERs to be installed in distribution systems respectively.

3. MONARCH BUTTERFLY OPTIMISATION

The MBO is inspired from the migration behaviors of monarch butterflies of North America. The monarch butterfly flutter migrates from region-1 to region-2 in the month of April and from region-2 to region-1 in September. During this process they keep producing offspring which replace their parents. The MBO technique consists basically of two updating operators, migration operator, and butterfly adjustment operator. In migration, monarch butterflies follow some set of rules [11]: 1) complete monarch flutter lies in both regions; 2) offspring are produced in region 1 or 2 only; 3) the size of monarch flutter remains constant; and 4) few monarch butterflies are not upgraded by upgrading operators.

3.1 Migration operators (MO)

Suppose, the population of monarch flutter remains in region-1, i.e., *subpopulation*-1 *(N_{P1})*, is determined as *ceil(p_r*N_P)*. Similarly, *subpopulation*-2 *(N_{P2})* can be considered for region-2 and calculated as N_P-N_{P1}. Here, N_P and p_r are representing the complete monarch butterfly population and ration of monarch butterfly in region-1. The mathematical representation of the migration process can be expressed as

$$Z_{x,k}^{t+1} = Z_{r1,k}^{t} \tag{11}$$

here, $Z_{x,k}^{t+1}$ represents k^{th} element of Z_x in generation *t*+1. Similarly, $Z_{r1,k}^{t}$ represents the k^{th} element of Z_{r1} for the current generation *t*. *r1* is a randomly picked individual from subpopulation 1 (N_{P1}). If $r \le pr$, the value of $Z_{x,k}^{t+1}$ is updated by (11) otherwise (12); where *r* is calculated as $r = rand \times peri$ in which *peri* is migration operator set to 1.2 and *rand* is a random value generated between 0 to 1 [11].

$$Z_{x,k}^{t+1} = Z_{r2,k}^{t} \tag{12}$$

where, $Z_{r2,k}^{t}$ represents the k^{th} element of Z_{r2} in generation *t*. *r2* is a randomly selected individual from *subpopulation 2 (N_{P2})*.

3.2 Butterfly adjustment operator (BAO)

In BAO, if *rand ≤ pr* then butterfly element at y^{th} position $Z_{y,k}^{t+1}$ is modified as (13) otherwise (14).

$$Z_{y,k}^{t+1} = \; Z_{best,k}^{t} \tag{13}$$

$Z_{best,k}^{t}$ represents k^{th} element of fittest butterfly found in t^{th} generation.

$$Z_{y,k}^{t+1} = Z_{r3,k}^{t} \tag{14}$$

$Z_{r3,k}^{t}$ denotes the k^{th} element of Z_{r3} where $r_3 \in \{1,2,.....,NP_2\}$. For this condition, if *rand > BAR* then it is further updated as

$$Z_{y,k}^{t+1} = Z_{y,k}^{t+1} + \alpha \; (dZ_k - 0.5) \tag{15}$$

here, *BAR* and *dZ* represent butterfly adjustment rate, and walk step size of butterfly *y* that can be produced from Levy flight as $dZ = levy(Z_y^t)$. The weighting factor α is calculated as $\alpha = W_{max}/t^2$ where W_{max} is the maximum walk step.

4. OPTIMAL INTEGRATION OF DER USING MBO

In this section, the application of MBO techniques is explained. The decision variables of the problem are DER sites and sizes. The number of DGs N_{DG} is assumed to be deployed in a system then the length of an individual will be $2N_{DG}$. The structure of monarch butterfly used in this work, containing all optimization variables, is shown in Fig. 1.

Fig. 1. Structure of an individual moth

5. SIMULATION AND RESULTS

5.1 Validation of MBO for power loss minimization

To demonstrate and validate the ability of MBO to solve dispatchable DG integration problems, an already existing simple power loss minimization problem is solved for a benchmark 33-bus test distribution system. This is a 12.66 kV radial test distribution network with total real and reactive power demands of 3.715MW, and 2.300 MVAr respectively [12]. For validation, a comparison of simulation results obtained by MBO and some of the existing optimization methods is presented in Table I. The comparison shows that MBO has ability to provide promising results as compared to TLBO, Quasi-Oppositional TLBO (QOTLBO), GA/PSO, analytical, improved analytical (IA), exhaustive load flow (ELF) methods.

5.2 MBO for proposed DG integration problem

After establishing the MBO for power loss minimization, it is applied to solve the proposed renewable based DG integration problem for the same 33-bus distribution system. The information of hourly wind speed, solar irradiation and load demand are referred from [13, 14]. It is noticed that distribution systems are found to be in a small geographical area therefore the availability of solar irradiation and wind speed are assumed to be equally distributed across all the system buses. The uncertainty of generation and load has not been considered in this work instead a deterministic framework is adopted.

To investigate the effect of each renewable technology and their operation, following cases are formulated and solved by using MBO: *Case-1 base case (no DG); Case-2 optimal integration of WTs only, operating at unity power factor (OPF); Case-3 optimal mixed integration of WTs and PV, operating at unity power factor (UPF); and Case-4: optimal mixed integration of WTs operating at lagging power factor (LPF) and PV operating at UPF*.

TABLE I Comparison of MBO and some other existing optimization techniques

Method	**Optimal DG Nodes (Sizes in MW)**	**Losses (MW)**
TLBO [9]	30(1.186), 28(1.191), 12(1.183)	0.1246
GA/PSO [6]	32(1.200), 16(0.863), 11(0.925)	0.1034
QOTLBO [9]	30(1.199), 26(1.187), 13(1.083)	0.1034
IA [15]	30(0.720), 12(0.900), 06(0.900)	0.0811
Analytical [16]	25(0.770), 16(0.530), 06(1.730)	0.0795
ELF [15]	30(0.900), 24(0.900), 13(0.900)	0.0743
MBO	30(1.019), 25(0.694), 13(0.862)	0.0729

Now, the MBO technique presented in Section 3 and 4 is applied to determine optimal sites, sizes and mix of renewables, for the above designed cases. The comparison of simulation results obtained for these cases is presented in Table II. The table presents sites and sizes of different DGs along with annual energy loss, DG penetration and value of minimum node voltage of the system, observed in considered time duration.

Table II Simulation results for optimal allocations of different DGs, DG penetration and annual energy loss.

Case	DG type, site (sizes in kW)	DG Penetration (%)	Annual Energy Loss (MWh)	Loss Reduction (%)
Case-1	-	-	3493.27	00.00
Case-2	WT@16(1250) WT@29(1250) WT@32(0850)	47.92	1714	50.93
Case-3	PV@11(1461.4) WT@17(0500) WT@31(1500)	49.51	1616	53.74
Case-4	WT@07(0500) WT@15(0500) PV@32(896.4)	27.13	1144	67.25

From these cases, it is observed that the integration of DERs significantly reduced the annual energy loss of the system. The mixed power generation of PV and WTs, in Case-3, provides higher loss reduction as compared to Case-2. It could be due to the fact that wind power generation is high during light load hours during the night whereas peak demand occurs in the day time. The period of PV power generation in Case-3 almost matches with the peak load hours of the demand.

In Cases-2 and 3, the DGs are operated at UPF therefore reactive power support from the PV and WTs have not been provided. In Case-4, the optimal siting and sizing of two WTs operating at 0.85 LPF and one PV operating at UPF are determined. The simulation results show that the consideration of VAr support from WTs completely changed sites and sizes of renewables, as compared to Case-3. This is motivating the VAr support from DGs that provide highest loss reduction, even with low DG penetration as compared to case-3. The mean node voltage profiles of these cases are presented in Fig. 2 which shows that mean node voltage profiles of 24-hours are near to unity.

These case studies show that MBO generates effective and encouraging optimal solution when applied to dispatchable and non-dispatchable DG integration in distribution systems. The method provides a promising solution for utilities to ameliorate the power system performance in terms of power loss reduction and maintaining voltage profile.

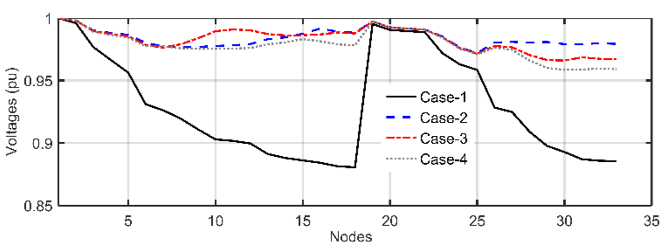

Fig. 2 Mean node voltages of the system for all cases

6. CONCLUSIONS

The article introduces a new optimization technique, i.e., MBO, to solve the DG integration problem of distribution systems. The technique effectively solves the optimal deployment of dispatchable DGs for power loss minimization, and renewable-based DGs for annual energy minimization, in a 33-bus system. The performance of this method is also compared with some of the existing method which shows that MBO has a promising solution searching ability. The methodology shows some better inherent properties to seek and explore the global optimal solution for complex real-life engineering optimization problems.

In future, the improved MBO can be applied to solve renewable integration problems of distribution problems by considering generation and load demand uncertainties.

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