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REDUCTION OF REAL POWER LOSS BY UNIFIED ALGORITHM

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Abstract

In this paper, we propose a new Unified Algorithm (UA) by combination of Variable mesh optimization algorithm (VMO) with Differential Evolution (DE) for solving reactive power problem. VMO has mainly three search operators, one for global exploration and two for local optima exploitation. DE is a simple yet commanding evolutionary algorithm for solving optimization problems. In all iteration VMO serve as the initial population of DE and obtains a population of more quality with this population VMO begins a new cycle. The proposed UA has been tested in standard IEEE 30 bus test system and simulation results show clearly about the better performance of the proposed algorithm in reducing the real power loss with control variables within the limits.

Keywords: Variable Mesh Optimization Algorithm; Differential Evolution; Optimal Reactive Power; Transmission Loss.

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1. Introduction

To till date various methodologies has been applied to solve the Optimal Reactive Power problem. The key aspect of solving Reactive Power problem is to reduce the real power loss. Previously many types of mathematical methodologies like linear programming, gradient method (Alsac et al., 1973; Lee et al., 1985; Monticelli et al., 1987; Deeb et al., 1990; Hobson, 1980; Lee et al., 1993; Mangoli et al., 1993; Canizares et al., 1996) [1-8] has been utilized to solve the reactive power problem, but they lack in handling the constraints to reach a global optimization solution. In the next level various types of evolutionary algorithms (Berizzi et al., 2012; Roy et al., 2012; Hu et al., 2010; Eleftherios et al., 2010) [9-12] has been applied to solve the reactive power problem. But each and every algorithm has some merits and demerits. One algorithm good in exploration means, it lacks in exploitation and another algorithm good in exploitation means it lacks in exploration. Some algorithms are good in exploration and exploitation but the speed of convergence is poor. In this work Variable mesh optimization algorithm **(**VMO) and

Differential Evolution **(**DE) algorithm are combined and the resulting mesh in all iteration of VMO serves as the initial population of DE and obtains a population of more quality. With this population VMO begins a new cycle. The proposed Unified Algorithm **(**UA) algorithm has been evaluated on standard IEEE 30 bus test system. The simulation results show that the proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

2. Objective Function

2.1.Active Power Loss

The objective of the reactive power dispatch problem is to minimize the active power loss and can be written in equations as follows:

$$F = P_L = \sum_{k\in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \qquad (1)$$

Where F- objective function, PL – power loss, gk - conductance of branch,Vi and Vj are voltages at buses i,j, Nbr- total number of transmission lines in power systems.

2.2.Voltage Profile Improvement

To minimize the voltage deviation in PQ buses, the objective function (F) can be written as:

$$F = P_L + \omega_v \times VD \qquad (2)$$

Where VD - voltage deviation, ω_v- is a weighting factor of voltage deviation.
And the Voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \qquad (3)$$

Where Npq- number of load buses

2.3.Equality Constraint

The equality constraint of the problem is indicated by the power balance equation as follows:

$$P_G = P_D + P_L \qquad (4)$$

Where PG- total power generation, PD - total power demand.

2.4.Inequality Constraints

The inequality constraint implies the limits on components in the power system in addition to the limits created to make sure system security. Upper and lower bounds on the active power of slack bus (Pg), and reactive power of generators (Qg) are written as follows:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \qquad (5)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \qquad (6)$$

Upper and lower bounds on the bus voltage magnitudes (Vi) is given by:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \qquad (7)$$

Upper and lower bounds on the transformers tap ratios (Ti) is given by:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \qquad (8)$$

Upper and lower bounds on the compensators (Qc) is given by:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \qquad (9)$$

Where N is the total number of buses, Ng is the total number of generators, NT is the total number of Transformers, Nc is the total number of shunt reactive compensators.

3. Variable Mesh Optimization

Variable mesh optimization algorithm (VMO) (Puris et al., 2011) [13] is a metaheuristic in which the population is sprinkled as a mesh. This mesh is self-possessed of Z nodes $(m_1, m_2, .., m_z)$ that represent solutions in the exploration space. Each node is coded as a vector of M floating point numbers $m_i = \left(g_1^i, g_2^i, .., g_j^i, .., g_i^M\right)$ that denote the solution to the optimization problem. In the exploration progression developed by VMO, two operations are accomplished: the expansion and contraction procedures. During the expansion, new nodes are produced in the direction of local extreme, the global end and to the edge nodes. Based on an exclusive strategy, nodes are ordered bestowing to their quality in uphill order. Cleaning adaptive operator is then applied; each node is compared to its heirs eliminating those that do not surpass a threshold. The value of this threshold can be calculated as:

$$\varepsilon_j = \begin{cases} \frac{range(k_j,l_j)}{4} if\ d < 0.149\ \%\ D \\ \frac{range(k_j,l_j)}{8} if\ 0.149\ \%\ D \leq d < 0.29\%\ D \\ \frac{range(k_j,l_j)}{16} if\ 0.29\ \%\ D \leq d < 0.59\%\ D \\ \frac{range(k_j,l_j)}{50} if\ 0.59\ \%\ D \leq d < 0.79\%\ d \\ \frac{range(k_j,l_j)}{100} if\ d \geq 0.79\%\ D \end{cases} \qquad (10)$$

Where D and d denote a maximum number of fitness evaluations allowed and the existing number of fitness evaluations. In addition, the range $\left(k_j, l_j\right)$ denotes the domain boundaries of each component. The node generation process at each cycle comprises the following steps:

a. Arbitrarily produce Z nodes for the primary mesh.
b. Produce nodes toward the local best.
c. Produce nodes toward the global best.
d. Produce nodes from nodes in the mesh boundary.

VMO algorithm

Start
Arbitrarily produce Z nodes for the primary mesh

Select the global best in the primary mesh
Repeat
For each node in primary mesh do
Find its closest k nodes by their spatial locations
Select the finest neighbour as per the fitness values
If present node is not the local best then
Produce a new node toward the local best
End if
end for
For each node in primary mesh but the global best do
Produce a new-fangled node toward the global best
End for
Produce nodes from nodes in the mesh frontier
Categorize nodes according to their fitness values
Smear the an adaptive clearing operator
Pick Z best nodes to build the primary mesh for the subsequent iteration
If needed an arbitrarily generate new nodes so as to complete the initial mesh for the following iteration
Is stop criterion is met, then
end

4. Differential Evolution

In Differential Evolution (DE) (Price et al., 2006; Storn et al., 2013; Epitropakis et al., 2011) [14-16] the population is created by common sampling within the stipulated minimum and maximum bounds. After the start of creating population, DE travel into the iteration process where the progressions like, mutation, crossover, and selection, are followed. DE employs the mutation strategy to generate a mutant vector D. And the strategies are listed as follows:

"DE/best/1":

$$D_i = Y_{best} + H(Y_{s1} - Y_{s2}) \quad (11)$$

"DE/current-to-best/1":

$$D_i = Y_i + H(Y_{best} - Y_i) + H(Y_{s1} - Y_{s2}) \quad (12)$$

"DE/best/2":

$$D_i = Y_{best} + H(Y_{s1} - Y_{s2}) + H(Y_{s3} - Y_{s4}) \quad (13)$$

"DE/rand/1":

$$D_i = Y_{s1} + H(Y_{s2} - Y_{s3}) \quad (14)$$

"DE/current-to-rand/1":

$$D_i = Y_i + H(Y_{s1} - Y_i) + H(Y_{s2} - Y_{s3}) \quad (15)$$

DE/rand/2":

$$D_i = Y_{r1} + H(Y_{s2} - Y_{s3}) + H(Y_{s4} - Y_{s5}) \quad (16)$$

Where the indices s1, s2, s3, s4, and s5 are homogenous different integers from 1 to N, Y_{best} denotes the best individual obtained so far D_i&Y_i are the ith vector of D and Y, rand indicates the term randomly and H is the constant respectively.

The crossover operator is performed to produce a trial vector G_i according to each pair of Y_i and D_i after the mutant vector D_i is generated. The most Enhanced strategy is the binomial crossover described as follows:

$$g_{ij} = \begin{cases} d_{i,j} if rand(0,1) \leq E_r \; or \; l = l_{rand} \\ y_{i,j} otherwise \end{cases} \quad (17)$$

where E_r is called the crossover rate, l_{rand} is arbitrarily sampled from 1 to N, and $g_{i,j}$, $d_{i,j}$, and $y_{i,j}$ are the jth element of G_i, D_i, and Y_i, respectively.

Finally, DE utilize greedy mechanism to choose the best vector from each pair of Y_i and G_i. This can be defined as follows:

$$Y_i = \begin{cases} G_i if fitness(G_i) \leq fitness(Y_i) \\ Y_i otherwise \end{cases} \quad (18)$$

DE algorithm

Start
Initialize population
Estimate primary population
For i=0 to max-iteration do
Pick an arbitrary trial vectors
Produce offspring population
Calculate offspring population
Amalgamate parent and offspring population
If an offspring is superior than its parent then
Swap the parent by offspring in the subsequent generation
End if
End for
End

5. Proposed Unified Algorithm (UA) – Combination of VMO Algorithm and DE Algorithm

The Unified Algorithm **(**UA) metaheuristic employs VMO as the key core and insert the DE algorithm in order to augment the primary mesh of the subsequent iteration. The use of DE was decided to progress the superiority of the population at the end of the cleaning process done by VMO. The DE algorithm does not produce an arbitrary preliminary population but takes as its chief population the matrix resulting from the cleaning operation executed by VMO, giving out a population with greater quality individuals whose VMO starts a new-fangled iteration.

Start
Arbitrarily produce Z nodes for the primary mesh
Pick the global best in the initial mesh
Repeat

For each node in primary mesh do
Find its closest k nodes by their spatial locations
Pick the finest neighbour as per the fitness values
If present node is not the local best then
Produce a new-fangled node toward the local best
End if
End for
For each node in primary mesh but the global best do
Produce a new node toward the global best
End for
Produce nodes from nodes in the mesh frontier
Categorize nodes according to their fitness values
Smear the adaptive clearing operator
Select Z best nodes to build the primary mesh for the following iteration
DE call using VMO population
Stop criterion
End

6. Simulation Results

Validity of proposed UA algorithm has been verified by testing in IEEE 30-bus, 41 branch system and it has 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is taken as slack bus and 2, 5, 8, 11 and 13 are considered as PV generator buses and others are PQ load buses. Control variables limits are given in Table 1.

Table 1: Primary Variable Limits (Pu)

Variables	**Min.**	**Max.**	**category**
Generator Bus	0.90	1.11	Continuous
Load Bus	0.91	1.01	Continuous
Transformer-Tap	0.92	1.01	Discrete
Shunt Reactive Compensator	-0.10	0.30	Discrete

In Table 2 the power limits of generators buses are listed.

Table 2: Generators Power Limits

Bus	**Pg**	**Pgmin**	**Pgmax**	**Qgmin**	**Qmax**
1	96.00	49	200	0	10
2	79.00	18	79	-40	50
5	49.00	14	49	-40	40
8	21.00	11	31	-10	40
11	21.00	11	28	-6	24
13	21.00	11	39	-6	24

Table 3 shows the proposed UA approach successfully kept the control variables within limits. Table 4 narrates about the performance of the proposed UA algorithm. Fig 1 shows about the voltage deviations during the iterations and Table 5 list out the overall comparison of the results of optimal solution obtained by various methods.

Table 3: After optimization values of control variables

Control Variables	UA
V1	1.0508
V2	1.0412
V5	1.0278
V8	1.0364
V11	1.0702
V13	1.0513
T4,12	0.00
T6,9	0.01
T6,10	0.90
T28,27	0.91
Q10	0.10
Q24	0.10
Real power loss	4.2941
Voltage deviation	0.9091

Table 4: Performance of UA algorithm

Iterations	25
Time taken (secs)	6.72
Real power loss	4.2941

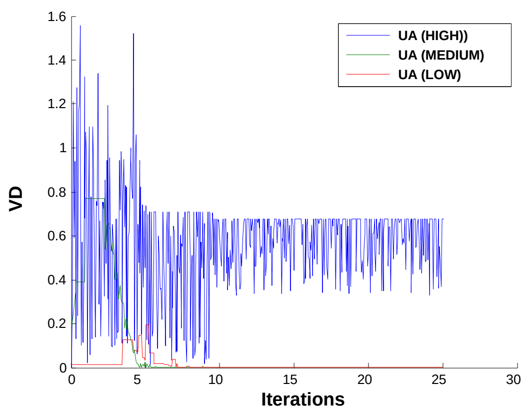

Figure 1: Voltage deviation (VD) characteristics

Table 5: Comparison of results

Techniques	**Real power loss (MW)**
SGA(Wu et al., 1998) [17]	4.98
PSO(Zhao et al., 2005) [18]	4.9262
LP(Mahadevan et al., 2010) [19]	5.988
EP(Mahadevan et al., 2010) [19]	4.963
CGA(Mahadevan et al., 2010) [19]	4.980
AGA(Mahadevan et al., 2010) [19]	4.926
CLPSO(Mahadevan et al., 2010) [19]	4.7208
HSA (Khazali et al., 2011) [20]	4.7624
BB-BC (Sakthivel et al., 2013) [21]	4.690
MCS(Tejaswini sharma et al.,2016) [22]	4.87231
Proposed UA	4.2941

7. Conclusion

In this paper, Unified Algorithm (UA) by combination of Variable mesh optimization algorithm (VMO) with Differential Evolution (DE) has been successfully implemented to solve Optimal Reactive Power Dispatch problem. The proposed (HA) algorithm has been tested in the standard IEEE 30 bus system. Simulation results show the robustness of proposed Unified Algorithm (UA) by combination of Variable mesh optimization algorithm (VMO) with Differential Evolution (DE) for providing better optimal solution in decreasing the real power loss. The control variables obtained after the optimization by UA are well within the limits.

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