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Hybrid - Particle Swarm Optimization and Differential Evolution for Reduction of Real Power Loss and Preservation of Voltage Stability Limits

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Abstract
In this paper, a Hybrid algorithm based on - Particle Swarm Optimization (PSO) and Differential Evolution (DE) is used for solving reactive power dispatch problem. It needs progressing the population to create the individual optimal positions by means of the PSO algorithm, and then the algorithm come in DE phase and progresses the individual optimal positions by smearing the DE algorithm. In order to comprehend co-evolution of DE and PSO algorithm, an information-sharing mechanism is presented, which progresses the capability of the algorithm to fence out of the local optimum. Additionally, in optimization procedure, we espouse the hybrid inertia weight stratagem, time-varying acceleration coefficients tactic and arbitrary scaling factor stratagem. The proposed Hybrid algorithm based on - Particle Swarm Optimization and Differential Evolution (H-PSDE) has been tested on standard IEEE 30, 57,118 bus test systems and simulation results show clearly about the better performance of the proposed algorithm in reducing the real power loss.
Keywords: Optimal Reactive Power; Transmission loss; Particle Swarm Optimization; Differential Evolution; Global Search; Local Search; Inertia Weight.

1. Introduction

Optimal reactive power dispatch (ORPD) problem is to diminish the real power loss and bus voltage deviation. Various mathematical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been implemented to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have complication in handling inequality constraints. The problem of voltage stability and collapse play a key role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is planned to advance the voltage stability index. In [13] Biogeography Based algorithm is proposed to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an enhanced evolutionary programming is used to solve the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by incorporating genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to calculate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based methodology is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes hybridization of Particle Swarm Optimization and Differential Evolution (HPSODE) for solving reactive power dispatch problem. The particle swarm optimization (PSO) algorithm is an evolutionary computation technique, and it was developed by Dr. Eberhart and Dr. Kennedy in 1995 [21, 22]. But PSO suffer in the premature problem of convergence, exclusively in solving the problems of high-dimensional complex functions. Until now, many researchers have projected numerous methodologies to overcome this problem, including improved parameters [23, 24] and hybrid algorithms [25, 26]. Differential evolution algorithm which was first planned by Storn and Price [27, 28, 29], and it is an efficient global optimizer in the continuous search domain. DE has greater search performance for many optimization problems with steady convergence rate at the beginning of the optimization. Yet, DE [30] has some inadequacies such as the slow convergence rate and effortlessly trapping in local optimum in the later period of evolution. In order to overcome the blemishes of PSO and DE in solving global optimization problems, we propose a Hybrid algorithm based on PSO and DE, called H-PSDE. H-PSDE starts with the normal PSO and amalgamated DE to grasp to the optimal solution. During optimization procedure, we espouse the hybrid inertia weight stratagem, time-varying acceleration coefficients stratagem and arbitrary scaling factor stratagem. The proposed algorithm H-PSDE has been evaluated in standard IEEE 30, 57,118 bus test systems. The simulation results show that our proposed approach outclasses all the entitled reported algorithms in minimization of real power loss.

2. Problem Formulation

The optimal power flow problem is a common minimization problem with constraints, and can be mathematically written in the following form:

Minimize f(x, u) (1)

subject to g(x,u)=0 (2)

and

$h(x, u) \leq 0$ (3)

where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \quad (4)$$

The control variables are the generator bus voltages, the shunt capacitors/reactors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \quad (5)$$

or

$$u = \left(V_{g1}, \ldots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \quad (6)$$

Where ng, nt and nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

3. Objective Function

3.1. Active power loss

The objective of the reactive power dispatch is to diminish the real power loss in the transmission network, which can be designated as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (7)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (8)$$

where g_k : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

3.2. Voltage profile improvement

For diminishing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (9)$$

where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (10)$$

3.3. Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \quad (11)$$

3.4. Inequality Constraints

The inequality constraints h(x,u) reflect the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad (12)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \quad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \quad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \quad (16)$$

Where N is the total number of buses, N_T is the total number of Transformers; N_c is the total number of shunt reactive compensators.

4. Standard particle swarm optimization

The basic principle of PSO as follows. Let *NP* symbolizes the population size of the swarm. At t generation, the position and velocity of the *i*-th particle are symbolized as $X_i = (x_{i1}, x_{i2}, \cdots x_{iD})$ and $V_i = (v_{i1}, v_{i2}, \cdots v_{iD})$ respectively. Let $P_i = (p_{i1}, p_{i2}, \cdots p_{iD})$ denotes its personal best position, and $P_g = (p_{g1}, p_{g2}, \cdots p_{gD})$ the global best position from the entire swarm. The modernizing rule is as follows:

$$v_{ij}^{k+1} = \omega v_{ij}^k + c_1 r_1 (p_{ij}^k - x_{ij}^k) + c_2 r_2 (p_{gj}^k - x_{ij}^k) \quad (17)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (18)$$

Where c_1 and c_2 are positive constants and called acceleration coefficients, parameter r_1 and $r_2$are two random functions in the interval [0,1]. ω is inertia weight, it is given by

$$\omega = \omega_{max} - \frac{iter}{\max iter}(\omega_{max} - \omega_{min}) \quad (19)$$

Where *iter* is the current iteration number and max *iter* is the maximum number of allowable iterations, w_{max} and w_{min} are the initial and final values of the inertia weight, respectively. In general, w_{max}=0.89 and w_{min}=0.38.

5. Differential evolution

Differential Evolution (DE) algorithm is based on Darwinian evolution. In DE algorithm, the child population is created through the Mutation Operation. Select two individuals at arbitrary, x_{r1}, x_{r2} , from the existing population. A new experimental vector v_i is produced using (20),

$$v_i = x_{best} + F \cdot (x_{r1} - x_{r2}) \quad (20)$$

Where *F* is a scaling factor which controls the augmentation of the differential evolution (x_{r1}-x_{r2}).

***5.1. Crossover Operation*: Produce offspring u_i according to (21)

$$u_{ij} = \begin{cases} v_{ij} \; rand \le CR \| j = randj \\ x_{ij} \quad otherwise \end{cases} \quad (21)$$

Where $CR \in [0,1]$ is the crossover probability and *randj* is a arbitrarily designated index.

***5.2. Selection Operation*: The selection operation is an avaricious selection criterion, which determines whether the individual endures to the next generations. The selection operation is described as

$$x_i(t+1) = \begin{cases} u_i(t+1) f(u_i(t+1)) < f(x_i(t)) \\ x_i(t) \quad otherwise \end{cases} \quad (22)$$

Where *f*(*x*) is the fitness value of individual *x*.

6. Hybridization of Particle Swarm Optimization and Differential Evolution

The projected H-PSDE algorithm is hybrid of PSO and DE. H-PSDE algorithm starts the PSO algorithm up to the point where the individual optimal position P_i of each particle is modernised. And then form the individual optimal position P_i of each particle to a new swarm. Afterwards, the algorithm moves in the DE phase. Lastly, to realize co-evolution of DE and PSO, information sharing mechanism is familiarised. The method is recurrent iteratively till the optimum value is grasped. The key idea of H-PSDE exemplifies in the following three aspects.

6.1. Hybrid inertia weight stratagem

Inertia weight plays a vital role on the equilibrium between local optimum and global optimum, a larger one enables global exploration and a smaller tends to assist local exploration. Enthused by this, we design hybrid inertia weight strategy – the nonlinear changing inertia weight and arbitrary inertia weight in possibilities.

$$\omega = \begin{cases} \omega_{min} + (\omega_{max} - \omega_{min})\big(1 - S(n)\big) if rand > 0.51 \\ 0.58 - 0.19 \cdot rand(\,)\ otherwise \end{cases} \quad (23)$$

Where $n = h_{min} + 2h_{max} \cdot \frac{iter-1}{\max iter-1}$Sigmoid function $\frac{1}{1+e^{-n}}$, $h_{\max}$ and $h_{\min}$ are the maximum and the minimum input values of Sigmoid function, respectively. Many experimental studies [31] confirmed the algorithm gives the best result when $w_{\max}$=0.89, $w_{\min}$=0.38 and $h_{\max} = -h_{\max} = 5.8$.Thus, it can balance the capability of global and local searching of the H-PSDE algorithm and progress the convergence accuracy efficaciously.

6.2. Time-varying acceleration coefficients stratagem

In the direction of its individual and global best position, Acceleration coefficients c_1 and c_2 control the movement of each particle. Small values limit the movement of the particles, while large numbers will cause the particles to move away [32]. In view of those concerns, a time-varying acceleration coefficient is introduced for the PSO perception. The objective of this development is to augment the global search in the early period of the optimization and to boost the particles to converge toward the global optimal in the final period of the search.

$$c_1 = c_{11} + c_{12} \cdot cos\left(\frac{iter}{\max\ iter}\pi\right) \quad (24)$$

$$c_2 = c_{21} + c_{12} \cdot cos\left(\frac{iter}{max\ iter}\pi\right) \quad (25)$$

Where c_{11}, c_{12}, c_{21} and c_{22} are constants, the empirical findings settles that the algorithm can give the best result with $c_{11} = c_{21} = 1.31$, $c_{12} = c_{22} = 0.51$.

6.3. Random scaling factor stratagem

Scaling factor F is a vital parameter in DE algorithm, which can affect the convergence speed and the exploration ability. To prevent premature convergence and to ensure progress stability of HPSODE algorithm, we suggest an arbitrary scaling factor stratagem.

$$F = 0.31 + 0.23 \cdot\ rand() \quad (26)$$

6.4. Algorithm of H-PSDE

Step 1: Initialize population.
Let initialization iterative number be $k = 0$, initialization population size be NP, the termination iterative number be *Maxiter*. Calculate the fitness function for each particle, and let first generation P_i be initialization particles, and pick the particle with the greatest fitness value of all the particles as the P_g.
Step 2: The H-PSDE algorithm enters PSO phase.
Step 2.1: Modernize the velocities and positions of all the particles using (17) and (18).
Step 2.2: For each individual particle, if the fitness value is better than the best fitness value $P_i(t)$ in past, let the current particle's position, X_i, as P_i. Pick the particle with the best fitness value of all particles as theP_g^{pso}.
Step 3: The H-PSDE algorithm enters DE phase.
Step 3.1: Form the individual optimal position P_i of each particle to a fresh swarm. Implement mutation, crossover, and selection operation above mentioned for the new-fangled swarm.
Step 3.2: Modernize the global optimal positionP_g^{DE}.
Step 4: Information sharing. Compare the fitness values of, P_g^{pso} andP_g^{DE}. pick the minimum one between the two. Let the corresponding position value as P_g, which are the greatest results of H-PSDE algorithm currently. That is, put P_g as P_g^{pso} in subsequent velocity calculation of PSO phase and as x_{best} in subsequent mutation operation of the DE phase.
Step 5: Repeat steps 2-4 until a stopping criterion is met (or maximum number of iterations).

7. Simulation results

H-PSDE algorithm has been tested in the IEEE 30-bus, 41 branch system. It has a total of 13 control variables as follows: 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. The considered security constraints are the voltage magnitudes of all buses, the reactive power limits of the shunt VAR compensators and the transformers tap settings limits. The variables limits are listed in Table 1.

Table 1: Initial Variables Limits (PU)

Control variables	Min. value	Max. value	Type
Generator: Vg	0.92	1.12	Continuous
Load Bus: VL	0.94	1.04	Continuous
T	0.94	1.04	Discrete
Qc	-0.11	0.30	Discrete

The transformer taps and the reactive power source installation are discrete with the changes step of 0.01. The power limits generators buses are represented in Table 2. Generators buses are: PV buses 2,5,8,11,13 and slack bus is 1 and the others are PQ-buses.

Table 2: Generators Power Limits in MW and MVAR

Bus n°	Pg	Pgmin	Pgmax	Qgmin
1	98.00	51	202	-21
2	81.00	22	81	-21
5	53.00	16	53	-16
8	21.00	11	34	-16
11	21.00	11	29	-11
13	21.00	13	41	-16

Table 3: Values of Control Variables after Optimization and Active Power Loss

Control Variables (p.u)	H-PSDE
V1	1.0651
V2	1.0528
V5	1.0320
V8	1.0449
V11	1.0861
V13	1.0660
T4,12	0.00
T6,9	0.03
T6,10	0.90
T28,27	0.91
Q10	0.11
Q24	0.11
PLOSS	4.5285
VD	0.9071

Table 3 show that the projected approach succeeds in keeping the dependent variables within their limits.
Table 4 summarizes the comparison of results and it reveals about the best performance of the proposed HPSODE algorithm in reducing the real power loss .

Table 4: Comparison Results of Different Methods

METHODS	PLOSS (MW)
SGA (33)	4.98
PSO (34)	4.9262
LP (35)	5.988
EP (35)	4.963
CGA (35)	4.980
AGA (35)	4.926
CLPSO (35)	4.7208
HSA (36)	4.7624
BB-BC (37)	4.690
H-PSDE	4.5285

Secondly the proposed Hybrid algorithm H-PSDE is tested in standard IEEE-57 bus power system. The reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. The system variable limits are given in Table 5.
The preliminary conditions for the IEEE-57 bus power system are given as follows:

P_{load} = 12.422 p.u. Q_{load} = 3.339 p.u.
The total initial generations and power losses are obtained as follows:
$\sum P_G$ = 12.7729 p.u. $\sum Q_G$ = 3.4559 p.u.
P_{loss} = 0.27450 p.u. Q_{loss} = -1.2249 p.u.
Table 6 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after H-PSDE based optimization which are within the acceptable limits. In Table 7, shows the comparison of optimum results obtained from proposed H-PSDE with other optimization techniques. These results indicate the robustness of proposed H-PSDE approach for providing better optimal solution in case of IEEE-57 bus system.

Table 5: Variable limits

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50

Voltage And Tap Setting Limits					
vgmin	vgmax	vpqmin	vpqmax	tkmin	tkmax
0.5	1.0	0.91	1.01	0.5	1.0

Shunt Capacitor Limits			
Bus no	18	25	53
Qcmin	0	0	0
Qcmax	10	5.2	6.1

Table 6: control variables obtained after optimization

Control Variables	H-PSDE
V1	1.1
V2	1.059
V3	1.040
V6	1.018
V8	1.031
V9	1.017
V12	1.025
Qc18	0.0757
Qc25	0.231
Qc53	0.0581
T4-18	1.011
T21-20	1.078
T24-25	0.952
T24-26	0.939
T7-29	1.079
T34-32	0.938
T11-41	1.011
T15-45	1.032
T14-46	0.911
T10-51	1.021
T13-49	1.059
T11-43	0.910
T40-56	0.900
T39-57	0.951
T9-55	0.952

Table 7: comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [38]	0.25902	0.30854	0.27858
2	CGA [38]	0.25244	0.27507	0.26293
3	AGA [38]	0.24564	0.26671	0.25127
4	PSO-w [38]	0.24270	0.26152	0.24725
5	PSO-cf [38]	0.24280	0.26032	0.24698
6	CLPSO [38]	0.24515	0.24780	0.24673
7	SPSO-07 [38]	0.24430	0.25457	0.24752
8	L-DE [38]	0.27812	0.41909	0.33177
9	L-SACP-DE [38]	0.27915	0.36978	0.31032
10	L-SaDE [38]	0.24267	0.24391	0.24311
11	SOA [38]	0.24265	0.24280	0.24270
12	LM [39]	0.2484	0.2922	0.2641
13	MBEP1 [39]	0.2474	0.2848	0.2643
14	MBEP2 [39]	0.2482	0.283	0.2592
15	BES100 [39]	0.2438	0.263	0.2541
16	BES200 [39]	0.3417	0.2486	0.2443
17	Proposed H-PSDE	0.22252	0.23129	0.23107

Then H-PSDE has been tested in standard IEEE 118-bus test system [40] .The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95, -1.1 per-unit., and on load buses are 0.95, -1.05 per-unit. The limit of transformer rate is 0.9, -1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 8, with the change in step of 0.01.

Table 8: Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results of 50 trial runs have been list in Table 9 and the results clearly show the better performance of proposed algorithm.

Table 9: Comparison results

Active power loss (p.u)	BBO [41]	ILSBBO/ strategy1 [41]	ILSBBO/ strategy1 [41]	Proposed H-PSDE
min	128.77	126.98	124.78	118.98
max	132.64	137.34	132.39	122.95
Average	130.21	130.37	129.22	119.91

8. Conclusion

H-PSDE algorithm has been successfully applied for solving Optimal Reactive Power Dispatch problem. H-PSDE based optimal power Reactive Power Dispatch problem has been tested in standard IEEE 30, 57,118 bus systems. Performance comparisons with well-known population-based algorithms give inspiring results. H-PSDE emerges positively to find good solutions when compared to that of other algorithms. The simulation results presented in previous section demonstrate the capability of H-PSDE methodology to arrive at near global optimal solution.

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