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Enhancement of Voltage Deviationin a Power Systemby Rectifying OPF Troubles

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Abstract-This paper presents an evolutionary based approach to solve the optimal power flow (OPF) problem. For optimal settings of OPF control variables, the proposed approach utilizes Particle Swarm Optimization (PSO) algorithm. On standard IEEE 30-bus test system is observed and tested with various objective functions like voltage deviation enhancement and voltage profile improvement in this proposed approach. The outcome of IPSO-TVAC method has quality convergence attribute. Furthermore it shows the possible of the proposed approach and illustrates its usefulness and toughness to solve the OPF problem for the systems considered. The proposed approach simulation results are lesser than other optimization algorithms reported in the literature.

Key words-*Voltage Deviation, Particle Swarm Optimization (PSO), Optimal Power Flow (OPF), Time Varying Acceleration Coefficients (TVAC).*

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I.INTRODUCTION

The problem of optimal power flow has sustained great observation. It is of present notice of numerous utilities and it was decided as one of the greatest functional necessity. The main focus of OPF solution is to optimize a specified objective function through optimal alteration of the control variables of power system while satisfy the different constraints of inequality and equality constraints.

Some traditional optimization methods have been used for solving the OPF problem. Further conversations on these methods are presented in [1- 2].Most of the traditional optimization methods concern with gradient-based optimization and sensitivity analysis algorithms through linearizing the objective function and the system constraints throughout an operating point. But OPF problem is a multi-modal and highly non-linear optimization problem. So local optimization methods, which are well developed, are not appropriate for such problem and also there is no standard to determine whether a local solution is also the global solution. Thus conventional optimization methods could not capable of identifies the global optimum. On the other hand, various mathematical assumptions like analytical, convex and differential objective functions have put to clarify the trouble. Though OPF problem is an optimization problem among in general, common non-smooth, non convex and non-differentiable objective functions. To overcome these drawbacks it is necessary to improve optimization methods that are systematic to conquer these disadvantages and manage such difficulties.

To defeat the boundaries of classical optimization techniques, newly evolutionary optimization techniques have been employed to solve OPF problem. An extensive diversity of heuristic optimization techniques have been used like simulated annealing [3], tabu search [4], genetic algorithm [5,6], Differential evolution [7] , hybrid DE [8]and particle swarm optimization [9] .For further research in this direction the outcomes are informed in the literature and those are cheering and promising.

PSO method has the pliability to intensify both local and global exploration abilities [10]. It is noted that actual PSO experience from premature convergence, mainly for problems with multiple local optimums [11, 12]. Cognitive and social component of two stochastic acceleration components direct the particles in the actual PSO algorithm to the optimum point. Social component stroll the particles around the search space and manage the global search ability, cognitive component manage local search ability. The significant task in PSO for solution quality is tuning the cognitive and social components. The best combination of those components has been found by a lot of researchers [10, 13].To resolve non-convex and non-continuous optimization problem a new iteration PSO with time varying acceleration coefficients method is proposed in this paper. Formation of TVAC leads a suitable balance among the social and cognitive components in the first phase and final iterations [11].By using IPSO the solution quality has been improved and also it avoids being trapped into local optimum [14].

The rest of the paper is organized as follows: Section 2 provides the mathematical formulation of the OPF problem. Section 3 explains about the over view of PSO and implementation of proposed IPSO-TVAC algorithm. Simulation results are given in section 4. Finally conclusions are given in Section 5.

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II. FORMULATION OF OPF PROBLEM

The objective of OPF problem is to optimize steady state performance of a power system in terms of an objective function while satisfy the equality and inequality constraints. Equality constraint signifies typical load flow equations. The constraints on control and dependent variables are inequality constraints. Except at the slack bus generator real power outputs (P_G) and generator voltages (V_G) are continuous variables and transformer tap settings and reactive power injections of the shunt compensators (Q_C) are discrete variables.

A. Objective function

The objective function of OPF is to minimize the total cost; if J is considered as the objective function, it is mathematically stated as

$$J= \sum_{i=1}^{N} Fi\ (Pi) \qquad (1)$$

Where Fi is the ith unit total cost, Nis the number of power generation units and P_i is the power output of ith unit. The production cost of ith generation unit is defined as:

$$F_i\ (P_i) = a_i P^2_{Gi} + b_i P_{Gi} + C_i \qquad (2)$$

The fuel cost coefficients of the i^{th} generating unit are a_i, b_i and c_i and the real power output of the i^{th} generating unit is P_{Gi}. The total cost must be minimized subject to following constraints.

$$V_{G_i}^{min} \le V_{G_i} \le V_{G_i}^{max}, \quad i = 1, \ldots, N_G \qquad (3)$$

$$P_{G_i}^{min} \le P_{G_i} \le P_{G_i}^{max}, \quad i = 1, \ldots, N_G \qquad (4)$$

$$Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max}, \quad i = 1, \ldots, N_G \qquad (5)$$

$$T_i^{min} \le T_i \le T_i^{max}, \quad i = 1, \ldots, N_T \qquad (6)$$

$$Q_{C_i}^{min} \le Q_{C_i} \le Q_{C_i}^{max}, \quad i = 1, \ldots, N_C \qquad (7)$$

$$V_{L_i}^{min} \le V_{L_i} \le V_{L_i}^{max}, \quad i = 1, \ldots, N_{PQ} \qquad (8)$$

$$S_{L_i} \le S_{L_i}^{max}, \quad i = 1, \ldots, N_L \qquad (9)$$

During the IPSO-TVAC algorithm process control variables are randomly generated. If control variables are not within the feasible range their limits updated using (10).

$$u_i = \begin{cases} u_i^{max} & \text{if } u_i > u_i^{max} \\ u_i^{min} & \text{if } u_i < u_i^{min} \end{cases} \qquad (10)$$

Thus proposed method satisfy the inequality constraints and the objective function and it can be modified as

$$F = \begin{cases} F_T & \text{if x is feasible} \\ f_{max} + CV & \text{otherwise} \end{cases} \qquad (11)$$

Where CV is the overall constraint violation and f_{max} is the worst feasible solution in the population, CV can be given as

$$CV = \max(0, P_{G,slack} - P_{G,slack}^{max}, P_{G,slack}^{min} - P_{G,slack}) + \sum_{i=1}^{N_{PQ}} \max(0, V_i - V_i^{max}, V_i^{min} - V_i) + \sum_{i=1}^{N_G} \max(0, Q_{Gi} - Q_{Gi}^{max}, Q_{Gi}^{min} - Q_{Gi}) + \sum_{l=1}^{N_L} \max(|S_l| - S_l^{max}) \qquad (12)$$

III. IMPROVED PSO WITH TIME VARYING ACCELERATION COEFFICIENTS METHOD

A. Typical particle swarm optimization

In 1995 Kennedy and Eberhart introduced swarm intelligence based PSO algorithms for the earliest period [15].The swarm behaviors modelled by PSO birds flocking and fishes schooling. In an N-dimensional solution space PSO starts with a fixed number of randomly initialized particles. A particle has position vector and velocity vector. Pbest is defined as the best solution achieved by ith particle until the current iteration, gbest is defined as the best among (pbest) the entire particles. Updated velocity and position of each particle can be written as follows

$$V_{j,d}^{(k+1)} = wV_{j,d}^{k} + c_1 rand_1 (Pbest_{j,d}^{k} - X_{j,d}^{k}) + c_2 rand_2 (Gbest_{j,d}^{k} - X_{j,d}^{k}) \qquad (13)$$

$$X_{j,d}^{(k+1)} = X_{j,d}^{k} + C\, V_{j,d}^{(k+1)} \qquad (14)$$

Where $V_{j,d}^{k}$ is the velocity of the j^{th} particle in the d^{th} dimension at iteration k, $Pbest_{j,d}^{k}$ is the own best position of particle j in the d^{th} dimension until iteration k,$Gbest_{j,d}^{k}$ is the best particle in the swarm in the d^{th} dimension at iteration k, c2 is social component acceleration coefficients, c1 is cognitive component acceleration coefficients, $X_{j,d}^{k}$ d,k,j gives the dimension, position of particle and iteration, k is the current iteration, rand1 and rand2 are the random numbers involving 0 and 1 and they are uniformly distributed, C is the constriction factor using (15), w is the inertia weight and it updated using (16)

$$C = \frac{2}{\left(2 - \phi - \sqrt{\phi^2 - 4\phi}\right)} \qquad (15)$$

$$w = W_{max} - \frac{(W_{max} - W_{min})}{G_{max}} * G \qquad (16)$$

Where G_{max} is maximum number of generation, W_{max} and W_{min} are final and initial values of inertia weight and G is current generation. In order to maintain the travelling of particles, velocity of each particle obtained in (13) is controlled by their lower and upper limits .This is given in (17)

$$V_d^{min} \le V_d \le V_d^{max} \qquad (17)$$

In d^{th} dimension V_d^{min} andV_d^{max} is the velocity minimum and maximum and those are calculated by using (18) and (19)

$$V_d^{max} = \frac{\left(x_d^{max} - x_d^{min}\right)}{K} \qquad (18)$$

$$V_d^{min} = -V_d^{max} \qquad (19)$$

In d^{th} dimension K=5 is the limit to control the number of space [16]. Due to variety at the end of research is competent

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to alter the optimal solution in order to improve the PSO solution.

B. Implementation of IPSO-TVAC for OPF problem

The proposed approach is used to improve the global searching capability and also prevent premature convergence. The new position can be generated by using (20).

$$x_{j,d}^{k+1} = \begin{cases} x_{j,d}^{k+1} & \text{if rand } \leq C_r \\ Pbest_{j,d}^{k} & \text{otherwise} \end{cases} \quad (20)$$

Where crossover probability is C_r, c_1 and c_2 are set as 2.0.To avoid travelling of particles in the search space; always c_2 is greater than c_1. The flowchart of proposed IPSO-TVAC algorithm is shown in Fig 1.

IV.RESULTS

In this section the proposed approach is applied on IEEE 30-bus standard test systems with different objective function to solve OPF problem and the results are compared with those obtained by other algorithms. Newton-Rapshonmethod with MATPOWER software package version 4.0b4 [24] is utilized for calculating power flow. The following values are selected in this proposed approach:
W_{max}=0.9; W_{min}=0.4; c_{1i}, c_{2f} =2.5; c_{1f}, c_{2i} = 0.2; C_r=0.6; N_p=50; GEN=300

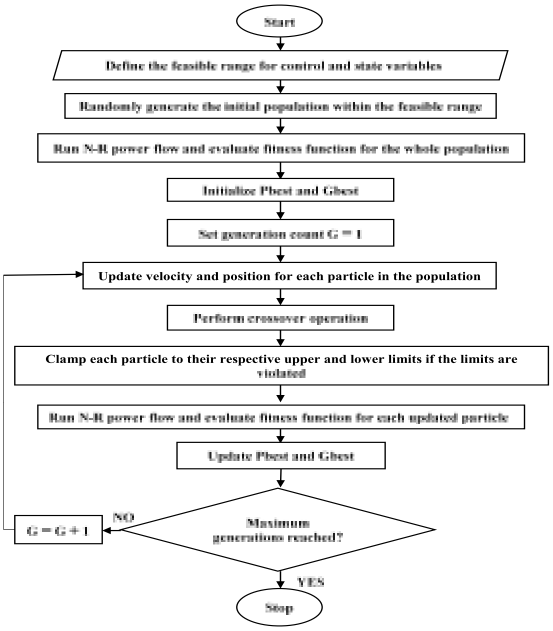

Fig. 1 IPSO-TVAC algorithm for solving OPF

The system bus data and line data are taken in [17-18].The system has four transformers with off-nominal tap ratio in lines 6-9, 6-10, 4-12, and 28-27 , six generators at buses 1, 2,5, 8,11 and 13 and shunt VAR compensation buses selected are 10,12,15,17,20,21,23,24, and 29. To exhibit the efficiency and sturdiness different objective functions with several cases considered are to enhance the voltage deviation and to improve the voltage profile.

A. Case 1 Voltage Deviation improvements

Under normal operating conditions it is important to maintain the bus voltage at each bus, once load increases, when the system is being subjected to a disturbance. The non-optimized control variables could cause uncontrollable and progressive drop in voltage which ensures that an extensive voltage collapse.

During line outage, the outage of the transmission line connected between bus 2 and bus 6 was considered as the contingency state [19]. In this case voltage deviation is the important anxiety. So the objective function considered is improvement of voltage deviation as given in (21). The result of proposed approach 9.64v, maximum is 12.086v, standard deviation of 0.0049 p.u.and an average is

TABLE 1BEST CONTROL VARIABLES SETTING FORDIFFERENT TEST CASES OF VOLTAGE DEVIATION

Control Variables	IPSO-TVAC		PSO [20]	DE [21]	GSA [19]		HFPSO-NM [22]	BBO [23]
	Case 1	Case 2	Case 1	Case 1	Case 2	Case 1	Case 1	Case 1
P_{G2}(p.u)	0.481474	0.5478	0.4798	0.4899	0.385769	0.44918	0.48943	0.4906
P_{G5}(p.u)	0.295397	0.5	0.292	0.2228	0.183565	0.23962	0.21953	0.2177
P_{G8}(p.u)	0.192184	0.292773	0.245	0.2101	0.261251	0.1417	0.22497	0.2327

P_{G11}(p.u)	0.203721	0.220815	0.1151	0.1732	1.01048	0.17213	0.12739	0.1384
P_{G13}(p.u)	0.133333	0.333163	0.2	0.1243	0.157839	0.16008	0.10883	0.1198
V_{G1}(p.u)	1.0159	1.0089	1.0891	1.0777	1.0954	1.0982	1.04299	1.0185
V_{G2}(p.u)	1.0057	1.0072	1.0693	1.0668	1.0894	1.0876	1.02625	1.0048
V_{G5}(p.u)	1.02	1.0196	1.0464	1.0828	1.0876	1.093797	1.008692	1.0145
V_{G8}(p.u)	1.0092	1.0019	1.0465	1.0875	1.0996	1.08974	1.00558	1.0092
V_{G11}(p.u)	1.016	1.0786	1.0277	1.0597	1.0961	1.09999	1.037581	1.051
V_{G13}(p.u)	1.0166	1.0255	1.0294	1.0191	1.0551	1.1	0.980777	1.0184
T_{11}(p.u)	1.03	1.06	0.9694	0.9032	0.09684	0.900001	1.05227	1.0718
T_{12}(p.u)	0.9	0.9	0.9238	0.9656	1.0226	0.9	0.949785	0.9
T_{15}(p.u)	1	1.01	0.9467	0.9181	0.9373	0.9	0.93696	1
T_{36}(p.u)	0.95	0.94	0.982	0.9147	0.9147	1.00657	0.98242	0.971
Q_{C10}(p.u)	0.04	0.01	0.0162	1.7913	3.458	0.949999	0.036054	0.042
Q_{C12}(p.u)	0.04	0	0.0424	4.1849	1.0405	0.0499974	0.03024	0.037
Q_{C15}(p.u)	0.05	0.05	0.0256	4.9791	3.8668	0.0499999	0.06708	0.05
Q_{C17}(p.u)	0.01	0	0.0465	1.1993	0.8019	0.05	0.02471	0
Q_{C20}(p.u)	0.05	0.05	0.0348	4.364	2.314	0.04998	0.06773	0.05
Q_{C21}(p.u)	0.04	0.02	0.05	4.8026	4.3131	0.049989	0.0705	0.05
Q_{C23}(p.u)	0.05	0.05	0.0488	2.249	4.5468	0.049977	0.02802	0.05
Q_{C24}(p.u)	0.05	0.05	0.05	1.2199	1.1061	0.049999	0.11656	0.05
Q_{C29}(p.u)	0.01	0	0.05	0.8939	1.8337	0.0372317	0.03513	0.03
Cost($/hr)	813.093	910.153	801.16	807.5271	810.2661	806.6013	803.5257	805.7582
P_{G1}(p.u)	1.620939	1.034712	1.7553	1.7165	1.8556	1.770432	1.76179	1.7367
Vdev(p.u)	0.0964	0.1056	_	0.016299	0.018772	0.9	0.0859	0.0951
Ploss (p.u)	0.093048	0.094745	_	0.103142	0.111099	0.09916	0.09794	0.1018

Case 1-without line outage, Case 2-with line outage

TABLE 2BEST VOLTAGE VALUES FOR VOLTAGE PROFILE ENHANCEMENT

Bus no	Case 1	Case 2	Bus no	Case 1	Case 2	Bus no	Case 1	Case 2
1	1.0159	1.0089	11	1.016	1.0786	21	0.9993	0.9988
2	1.0057	1.0072	12	1.0075	1.0088	22	1.0002	0.9999
3	1.0026	1	13	1.0166	1.0255	23	1	1
4	0.9993	0.9994	14	0.9985	1	24	0.9951	0.9951
5	1.02	1.0196	15	1	1.0003	25	1.0056	1.0066
6	1.0001	1.0004	16	1.0006	1.0008	26	0.9878	0.9887
7	1	1	17	1.0009	1.0005	27	1.0209	1.0225
8	1.0092	1.0019	18	0.9939	0.9942	28	0.9965	0.9942
9	1	1.0093	19	0.9936	0.9939	29	1.004	1.0026
10	1.0082	1.0085	20	0.999	0.9993	30	0.9912	0.9911

9.81v.

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The best control variables setting for different test cases of voltage deviation is given in Table 1. The convergence characteristic of VD for without and with line outage is shown in Fig. 2 and Fig. 3 respectively. In this study the proposed approach shows the system optimization and enhancing the voltage deviation in the contingency condition is considered.

Voltage Deviation (VD) is defined as

$$VD = \sum_{K=1}^{nbus} |V_k - V_{dk}| \quad (21)$$

Where V_k = Voltage magnitude of bus k, n bus = No of buses, V_{dk} *is d*esired voltage magnitude of bus k usually equals 1.0 p.u

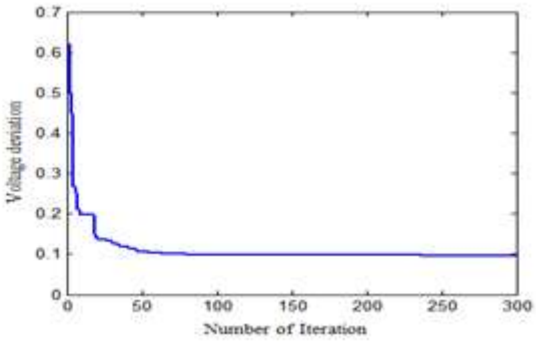

Fig. 2Convergence characteristic for VDwithout line outage

B.Case 2 Voltage Profile enhancement

The most important security and service quality indices is the bus voltage. Inview of OPF problem cost-based objective could result ina feasible solution that has unappealing voltage profile. Hence to improve voltage profile by minimizing the load bus voltage deviations from 1.0 per unit, a double objective function is considered. The objective function is expressed in [4].

$$J = \sum_{i=1}^{N} Fi\,(Pi) + w \sum_{i \in NL} |Vi - 1.0| \quad (22)$$

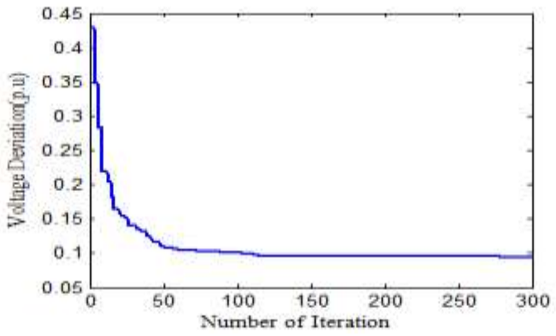

Fig. 3Convergence characteristic for VDwith line outage

Where w is the weighting factor set to balance among the two objectives to stop one objective over another. In this proposed approach to search for the optimal solution of the problem has been executed. Table2shows the best voltage for voltage profile enhancement. Fig. 4 shows the system voltage profile for case 2.Table 3 gives the comparison results obtained for voltage profile improvement. Table 4 illustrates the statistical analysis of simulation results case 1 for 30 trial runs. This demonstrate that the system to be quality solution and effective due to less value of standard deviation. It is clear that the voltage profile is greatly improved.

TABLE 3 COMPARISION RESULTS FOR CASE 2

Method	Voltage (deviation (p.u.)
IPSO-TVAC	0.0957(p.u)
BBO[23]	0.1020(p.u)
HFPSO-NM [22]	0.0859[a](p.u)

a-infeasible solution

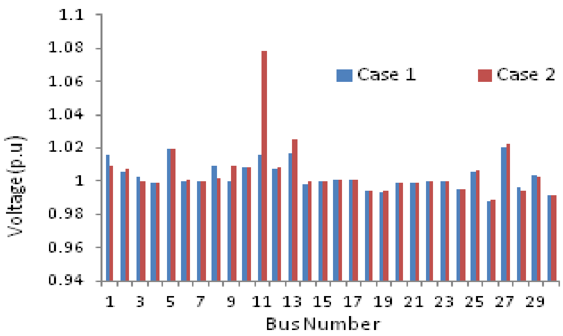

Fig. 4 System voltage profile for case 2

TABLE 4CASE 1 STATISTICAL ANALYSIS OF SIMULATION RESULTS FOR 30 TRIAL RUNS

Minimum(p.u)	0.093689
Maximum(p.u)	0.120862
Average(p.u)	0.098116
Std.deviation	0.004956
Ploss(MW)	7.1063
Qloss(MVAR)	16.1266
Time(s)	6269.556

V. CONCLUSION

In this paper, particle swarm optimization algorithm has been proposed, developed, and successfully applied to solve the optimal power flow problem. The OPF problem has been invented as optimization problem various objective functions have been considered to augment the voltage deviation and to improve the voltage profile in both normal and contingency condition. IEEE 30-bus test system has been tested and scrutinized for the proposed approach. The proposed method is proficient to obtain the lesser value of voltage deviation and voltage profile contrast to formerly reported methods. The complete analysis more than 300 trial runs prove that IPSO-TVAC has lesser variance in results and so is more dependable. Simulation results authenticate the pertinence of the IPSO-TVAC to resolution of OPF problems.

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