OPTIMAL REACTIVE POWER DISPATCH USING AUTONOMOUS GROUP PARTICLE SWARM BASED OPTIMIZATION

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Abstract- This paper presents Autonomous group Particle Swarm optimisation Algorithm(AGPSO), with dynamic weights, applied to scale back the important power loss during a system, up the voltage profile and thus enhancing the performance of power grid. Particle Swarm optimisation with elaborate study on weights for particle movements is employed. Management variables thought-about square measure Generator bus voltages, MVAR at electrical condenser banks, transformer tap settings and reactive power generation at generator buses. The best values of the management variables square measure obtained by determination the multi objective optimisation downside victimisation AGPSO rule programmed victimisation M writing in MATLAB platform. With the optimum setting for the management variables, Newton Rapson primarily based power flow is performed for two test systems, viz., IEEE 30 and IEEE 57 bus system . reduction of Real power loss ,improvement of voltage profile obtained and improvement in loadability margin area unit compared with the results obtained exploitation firefly,GRADE and Group Search Optimization(GSO) techniques.

Keywords: Multi objective optimization, AGPSO Algorithm, real power loss minimization, voltage profile improvement, loadability margin.

1. Introduction

Reactive power flow optimization enhance the voltage profile and additionally minimizes the active power loss. The flow of reactive power in a very power grid is controlled through generator voltages, transformer tap position and switch-able volt-ampere sources. An explicit combination of those generator voltages, transformer tap position positions and reactive power from electrical condenser banks result in optimized reactive power flow. The search space is multidimensional due to sizable amount of control variables. The quality of reactive power improvement increases with increase within the size of power grid.

Earlier, standard ways were used for resolution of reactive power flow improvement. These ways sometimes operate with single resolving that is then optimized. the traditional ways have a serious downside of leading towards local minima. Additionally the traditional ways don't with efficiency work for combination of variables. Time consumption of those ways is additionally terribly high. To beat these drawbacks computing ways like genetic algorithm [9,10,14], simulated annealing, Glow warm swarm [17], Particle Swarm Optimization[13], and colony optimization ways are wont to solve reactive power optimization problem..Shanmugalatha etal. [16] have used improvement for voltage security and reactive power optimization, applied to totally different share of loads. Basu.M and Vardharajan [8,25] use differential evolution to search out the optimized solution. Heuristic and evolution- ary approach are enforced by Bhattacharya and Goswami [4] to search out the optimum power flow solution. Particle Swarm optimization has been applied for reactive power improvement by Altaf et al. [2], Barun mandal [6] and, Biplab Bhattacharyya [7]. Hybrid PSO having some additional options of different search ways [18,21] or some distinctive features applied to PSO have additionally been applied.PSO search technique has been studied one by one to predict the optimized weights and factors for the search methodology [11,12]. Zhua et al. [28] uses fitness magnitude relation to calculate the weights for particle movement in search space. The approach projected during this paper uses Autonomous Group Particle Swarm Optimization (AGPSO) technique with dynamic weights. A test cases is conferred on IEEE 30 and IEEE 57 bus system and also the final optimum variable values are shown.

2. Power Flow Equations

The power flow equations describe the constraints governing the flow of power within the grid. These equations or constraints will be classified into equality and inequality constraints. The equality constraints are automatically satisfied through the load flow calculations. For inequality constraints to be satisfied, the program coding of Autonomous

Group Particle Swarm optimisation (AGPSO) Algorithm is employed. The inequality constraints square measure checked for violations throughout the execution of the program.

2.1 Mathematical Problem Formulation

The main objective of multi objective optimization is to minimize the active power loss in the transmission network, which is defined as follows:

$$f_1 = \min \sum_{n=1}^{nl} P_{loss} \tag{1}$$

Another objective of this problem is to improve the voltage profile which is formulated mathematically as follows,

$$f_2 = \sum_{i=1}^{n} \left| V_{max,spec} - V \right| \tag{2}$$

The overall objective function of the problem is thus formulated as follows,

$$f = \alpha(f_1) + \beta(f_2) \tag{3}$$

Where, P_{loss}= active power loss in the transmission network,

$V_{max,spec}$= is the maximum voltage specified for all the buses,

α and β are the penalty factors.

2.2. Constraints

2.2.1 Equality Constraints. The equality constraints include the real and reactive power constraints which are given as follows:

2.2.1.1 Real Power Constraint

$$P_i(V,\theta) = \sum_{j=1}^{n} V_i V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \tag{4}$$

Where, n = numbers of buses, except swing bus.
G_{ij}= mutual conductance between bus i and j.
B_{ij}= mutual susceptance between bus i and j.
Θ_{ij}= Load angle between bus i and j.
P_i =Real power injected into network at bus i.
V_i V_j= Voltage magnitude at bus i,j

2.2.1.2 Reactive Power Constraint

$$Q_i(V,\theta) = \sum_{j=1}^{n} V_i V_j (G_{ij}\sin\theta_{ij} + B_{ij}\cos\theta_{ij}) \tag{5}$$

Where, n= number of buses, except swing bus.
Q_i=Reactive power injected into network at bus i.

2.2.2 Inequality Constraints. The inequality constraints include the following,

2.2.2.1 Bus Voltage Magnitude Constraint

$V_{i,min} \le V_i \le V_{i,max}$; $i \epsilon N_B$:Total number of buses (6)

Where, V_i= Voltage magnitude at bus i.
N_B= Total number of buses

2.1.2.2 Generator Bus Reactive Power Constrain

$Q_{Gi,min} \le Q_{Gi} \le Q_{Gi,max}$; $i \epsilon N_g$ (7)

Where, Q_{Gi}= Reactive power generation at bus i.
N_g = Number of generator buses.

2.1.2.3 Reactive Power Source Capacity Constraints

$Q_{Ci,min} \le Q_{Ci} \le Q_{Ci,max}$; $i \epsilon N_c$ (8)

Where, Q_{Ci}= Reactive power generated by i^{th} capacitor bank.
N_C = No. of capacitor banks.

2.2.2.4 Transformer Tap Position Constraints:

$T_{k,min} \le T_k \le T_{k,max}$; $i \epsilon N_T$ (9)

Where, T_k = Tap setting of transformer at branch k.
N_T = No. of tap-setting transformer branches.

3. SWARM BASED OPTIMIZATION APPROACH

3.1 Standard Particle Swarm Optimization Algorithm

Standard Particle swarm optimization (Std. PSO) could be a population-based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy [13] in 1995, galvanized by social behavior of bird flocking or fish schooling. In PSO, every single resolution could be a "particle" within the search house. All of the particles have fitness values, that are evaluated by the fitness perform to be optimized, and have velocities that direct the flying of the particles. The particles fly through the problem house by following the present optimum particles.

PSO is initialized with a group of random particles (solutions) then searches for optima by change generations. In each iteration, every particle is updated by following 2 "best" values. the primary one is that the best resolution (fitness) it's achieved to this point. This value is named p best. Another "best" worth that's caterpillar-tracked by the particle swarm optimizer is that the best worth, obtained to this point by any particle within the population. This best worth could be a global best and referred to as g best. Throughout iterations, every particle adjusts its position and rate as follows:

$$v_q^{t+1} = w.v_q^t + C_1.rd.(pbest_q - x_q^t) + C_2.rd.(gbest - x_q^t) \quad (10)$$

$$x_q^{t+1} = x_q^t + v_q^{t+1} \quad (11)$$

Where,

C_1 is the Cognitive coefficient
C_2 is the Social Factor
rd is the random number
w is the inertial weight
x_q is the position vector
v_q is the velocity vector

3.2 Autonomous Group Particle Swarm Optimization Algorithm

In this paper, Std. PSO is changed by a mathematical model of distinct functions with various slopes, curvatures, and interception points area unit utilized to tune social and psychological feature constants of C1 and C2 parameters are given in Equation (2) to come up with particles of various behaviors to attain the specified solution. This modification leads the Std. PSO into a changed customary particle swarm optimisation algorithmic program named as Autonomous Group Particle Swarm optimisation (AGPSO). AGPSO is principally applied to alleviate the 2 major issues of trappings in local minima and slow convergence rate of std. PSO in calibration the parameters of reactive power equality and in equality constraints for a multi objective power system. Detailed description concerning AGPSO is available in [20] with the deserves of AGPSO compared with variants of PSO.

3.3 Algorithmic Steps for AGPSO Algorithm

Application of the AGPSO algorithmic rule for the optimimum reactive power dispatch, parameters the flowchart of which is shown in Figure. 1 is explained as follows

(i) Minimum and maximum values for control and state variables are set. Transformer tap positions are initiated. Random particles are generated.

$$x_i = [K_{ploss,i}, T_{1,i}, T_{2,i}, T_{3,i}, T_{4,i}]^T \; (19\times1) \text{ and } (25\times1) \quad (12)$$

(ii) Particles x_i are randomly split into some predefined autonomous groups (AGPSO1, AGPSO 2 and AGPSO 3) with beneficiary functions given in Table.1. The counter is initialized to 1 and it measures each iteration.

(iii) Load flow constraints are verified.

(iv) Load flow is executed for each and every particle exploitation Newton Raphson method. This gives the active power loss, i.e., the value of objective function or the fitness value for each particle.

(v) Calculate gbest, pbest, and the fitness (Eq. (10)) of each particle x_i at each iterationFor each particle, the coefficients C_1 and C_2 are updated exploitation its group's strategy from the table 1

(vi) Velocities V_i and positions of particles X_i will be updated exploitation Eqs. 10 and Eqs. 11. It should be noted that when the particle moves from the current position x_i to the new position x_{i+1} substituting into Eq.11, this results from the amendment in parameters of reactive power.

(vii) Based on the values of individual best, global best and random velocities, each particle is assigned a new position.

(viii) Stopping criteria is checked, if satisfied the search process stops and displays the result, else proceeds for the next iteration.

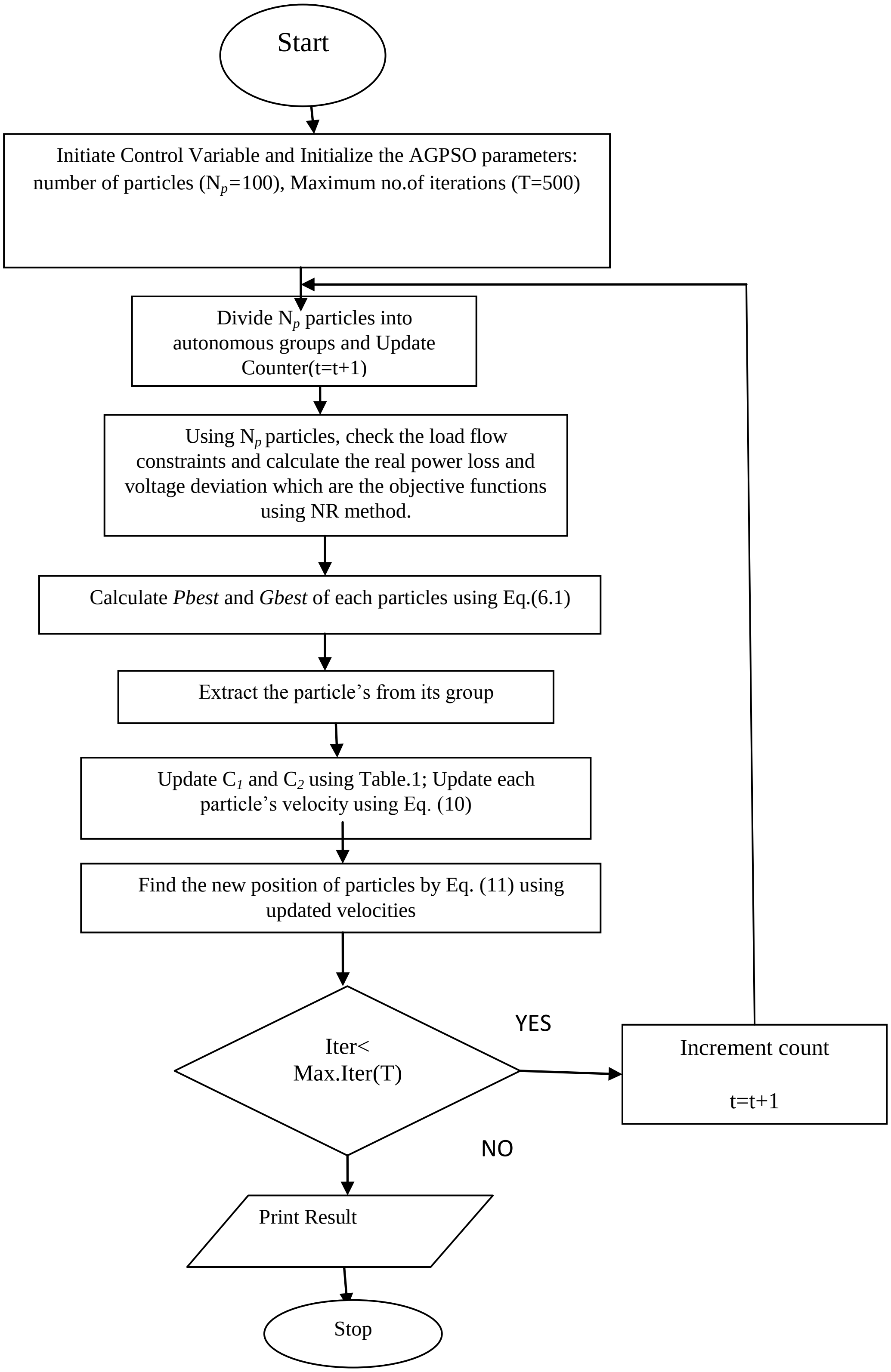


Figure 1. Flowchart of AGPSO algorithm for Multi Objective Optimal Reactive Power Dispatch

4 Results and Discussion

The effectiveness of AGPSO rule primarily based optimization technique is tested in IEEE 30-

bus and IEEE 57-bus test systems and the results are compared with the results obtained using firefly,GRADE and GSO algorithms. The proposed algorithm is developed in MATLAB 7 and run on a PC with INTEL i5 processor of 4GB RAM. For implementing AGPSO technique, 30 trials are performed in the above mentioned test systems.

Optimal Reactive Power Dispatch(ORPD) problem is formulated as a multi objective optimization problem subject to equality and inequality constraints. Real and Reactive power losses are considered as equality constraints. Inequality constraints comprise of generator bus voltages, transformer tap settings, and reactive power ratings at the capacitor banks and reactive power generation at generator buses.

The load flow analysis for the IEEE-30 and IEEE-57 Bus systems is performed using Newton-Raphson power flow method in MATLAB. The base case real power loss is obtained as 0.05660(MW) for IEEE-30 bus system and 0.278638(MW) for IEEE-57 bus system. The main objective function is presented to solve multi objective optimization problem to minimize real power losses and to improve the voltage profile. In this work attempt to also made to improve the loadability margin. To accomplish this weak most bus identified using sensitivity analysis method(21). Continution power flow is performed with the normal setting of the control variable and the loadability margin of the base case is found out. With the optimal setting of the control variable are obtained using various Bio-Inspired techniques. Continuation power flow is performed repeatedly PV curve is plotted in the weak most bus and loadability margin is obtained in each of the optimization techniques employed for getting the ORPD. It is found that loadability margin improves AGPSO based optimization techniques. It provides best results compared to the other techniques. The effectiveness of the algorithm is tested for three different loading condition as follows,

1. Light load-Half the normal load
2. Normal load- Rated Load
3. Heavy load- Double the rated load

4.1 Results in IEEE-30 Bus System

The IEEE 30-bus network consists of 6 generators at buses 1,2,5,8,11 and 13, 4 transformers with off nominal tap ratio, and 41 branches. The transformers are at the branches 6-9, 6-10, 4-12 and 28-27. The reactive power support is provided at the buses 10,12,15,17,20,21,23,24 and 29. Total real power demand is 2.834 p.u. at 100 MVA base. The line data , bus data, generator data and minimum and maximum limits for the control variables have been adopted from Lee k, Park Y and Ortiz J 1985[15]. The single line diagram of IEEE-30 bus system is presented in Figure 2.

The number of control variables considered for Optimal Reactive Power Dispatch in case of IEEE-30 bus system is 19. The control variables includes 6 generator bus voltage values (V_{G1}, $V_{G2,}$ $V_{G5,}$ $V_{G8,}$ $V_{G11,}$ V_{G13}), 4 values of transformer tap setting positions ($T_{6\text{-}9}$, $T_{6\text{-}10,}$ $T_{4\text{-}12,}$ $T_{27\text{-}28}$) and 9 injected reactive power values (Q_{10}, Q_{12}, Q_{15},Q_{17},Q_{20},Q_{21},Q_{23},Q_{24},Q_{29}).

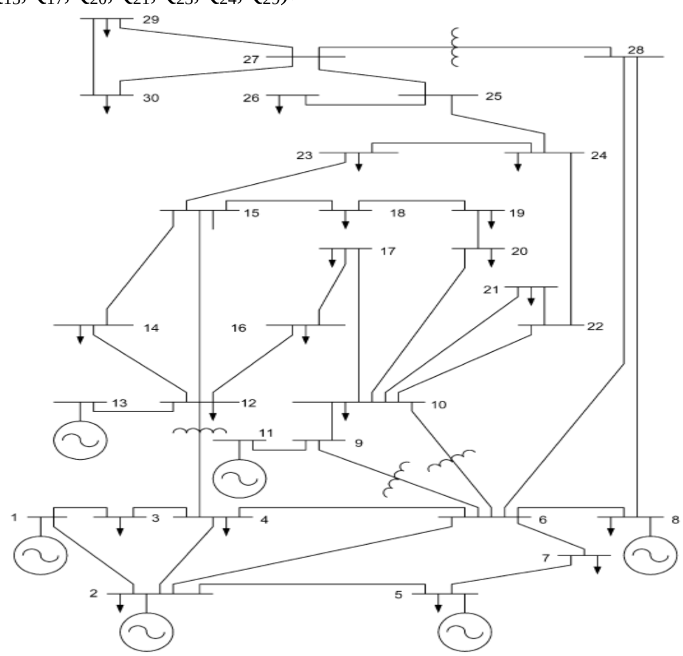


Figure 2. Single line diagram of IEEE 30 bus system

4.1.1 Comparision of Minimization of Real Power losses

A comparison of fitness value for various loading condition is provided in Table 1 and a comparison of the real power loss obtained using Firefly,GRADE, GSO and AGPSO algorithm under three loading condition is shown in the Table 2.

Table 1 Comparison of fitness value for the three loading conditions

Loading condition	Lightly loaded condition				Normal loaded condition				Heavily loaded condition			
Optimization Technique	Firefly	GRADE	GSO	AGPSO	Firefly	GRADE	GSO	AGPSO	Firefly	GRADE	GSO	AGPSO
Fitness Value	0.12732	0.043762	0.043761	0.02264	0.43534	0.20071	0.20069	0.11065	1.4924	0.54832	0.54832	0.36458

From Table 2, it can be seen that,real power loss reduction is more when AGPSO algorithm is used compared to conventional techniques such as firefly, GSO and GRADE.After 30 trials the real power losses obtained by ORPD using AGPSO algorithm is presented in Table 2.

Table 2 Comparison of real power loss for IEEE30 bus system

Loading condition	Lightly loaded condition					Normal loaded condition					Heavily loaded condition				
Optimization Technique	Base case	Firefly	GRADE	GSO	AGPSO	Base Case	Firefly	GRADE	GSO	AGPSO	Base Case	Firefly	GRADE	GSO	AGPSO
P_{loss}(p.u)	0.04265	0.04151	0.03952	0.03875	0.03753	0.0566	0.04612	0.04525	0.04501	0.04498	0.07371	0.07032	0.06978	0.06785	0.06323

4.1.2 comparision of optimum setting of control variable under different loading condition

The optimal values of the control variables after optimization for three loading conditions are shown in Table 3.

From Table 3 , it can be observed that,all control variables are set as per the optimum values obtained using AGPSO Algorithm and the values are within the specified limits.

4.1.3 COMPARISION OF IMPROVEMENT OF VOLTAGE PROFILE

A comparison of voltage levels before and after optimization for lightly loaded condition, normal loaded condition and heavy loaded condition is also presented in Figures 3, 4 and 5 respectively. The 30th bus of the IEEE 30 bus system is found to be the weakest bus from power flow results and hence voltage at 30th bus is compared to establish the effectiveness of AGPSO Algorithm is improving the voltage profile.

Figure 3. Comparison of voltage levels before and after optimization under light loaded condition for IEEE30 bus test system obtained using AGPSO Algorithm

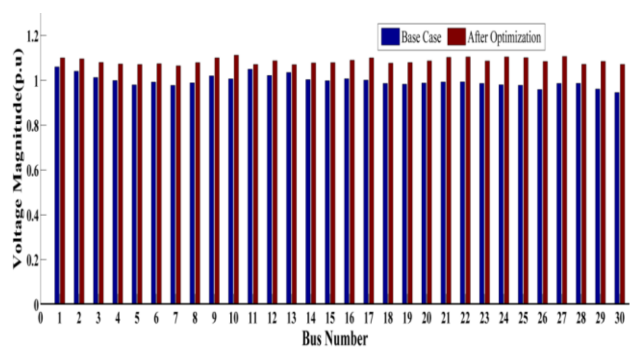
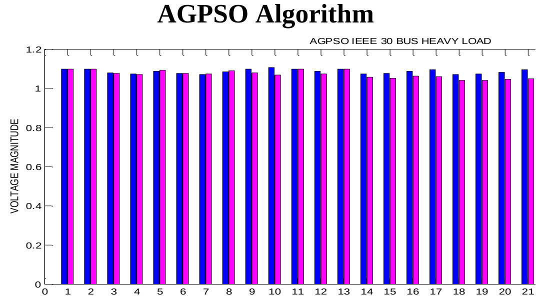


Figure 4. comparison of voltage levels before and after optimization under normal loaded condition for IEEE30 bus test system obtained using AGPSO Algorithm



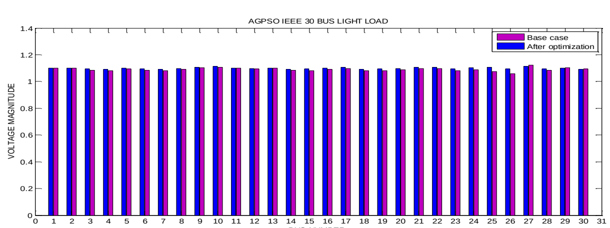


Figure 5. Comparison of voltage levels before and after optimization under heavy loaded condition for IEEE30 bus system obtained using AGPSO Algorithm

Table 3. Optimal values of the control variables in p.u. obtained using AGPSO algorithm for IEEE30 bus system

Control variables	Lightly loaded condition	Normal loaded condition	Heavily loaded condition
V_1(p.u)	1.1	1.1	1.1
V_2(p.u)	1.1	1.1	1.1
V_5(p.u)	1.1	1.1	1.1
V_8(p.u)	1.0988	1.1	1.0993
V_{11}(p.u)	1.1	1.1	1.1
V_{13}(p.u)	1.1	1.1	1.1
Q_{C10}(p.u)	0.255896	0.5	0.283567
Q_{C24}(p.u)	0.08713	0.2137	0.1451
$T_{6\text{-}9}$	1.0003	0.97082	0.99
$T_{6\text{-}10}$	0.99	1.0157	0.99
$T_{4\text{-}12}$	0.99	0.95	0.9812
$T_{28\text{-}27}$	0.99	0.95	0.9466
Q_{c12}(p.u)	0.0245	0.0215	0.056
Q_{c15}(p.u)	0.0178	0.0171	0.1990
Q_{c17}(p.u)	0.0500	0.0512	0.0518
Q_{c20}(p.u)	0.0335	0.0314	0.0415
Q_{c21}(p.u)	0.0403	0.0412	0.0486
Q_{c23}(p.u)	0.0269	0.0261	0.0462
Q_{c29}(p.u)	0.0195	0.0192	0.0385

It is noted that,from Figure 3,4 and 5 in all the loading conditions voltage profile improvement is optimum when controllers are tuned using AGPSO Algorithm.

4.1.4 Comparision of Improvement of Loadability Margin

The result of continuation power flow analysis before and after optimization for different loading conditions is presented. As the 30th bus of the IEEE-30 bus system is found to be the weakest bus, real power at bus number 30 is considered as load parameter in continuation power flow. The result of continuation power flow analysis before and after optimization for different loading conditions is presented.

The 30th bus of the IEEE-30 bus system is found as the weakest bus. This bus is considered as the candidate bus for load change in continuation power flow. Thus under various loading conditions the PV curve is obtained and the comparison of PV curve before and after optimization is done.

Light loaded condition

Under Light load condition the λ-V curves are as shown in Figure 6 for IEEE 30-bus system before and after optimization. The loadability margin has increased from 1.1792(p.u) to 3.6858 (p.u).

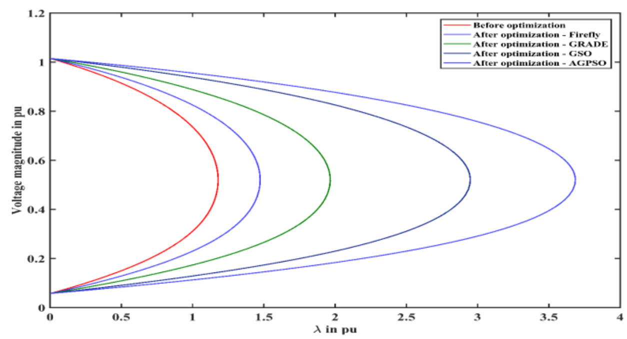


Figure 6. Comparison of λ V curves before and after optimization for light loading condition for IEEE 30 bus system obtained using AGPSO algorithm

Normal loaded condition

Figure 7 presents the λ-V curves at 30th bus of IEEE 30 bus system during normal load condition before and after optimization. It is observed that the loadability margin has increased from 0.7835 (p.u) to 2.4484 (p.u).

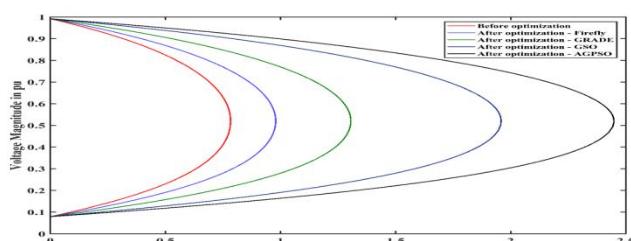


Figure 7. Comparison of λ V curves before and after optimization for normal loading condition for IEEE 30 bus system obtained using AGPSO algorithm

Heavy loaded condition

Under heavy load condition the λ-V curves are as shown in Figure 8 and the loadability margin has increased from 0.5460 (p.u) before optimization to 1.7062 (p.u) after optimization.

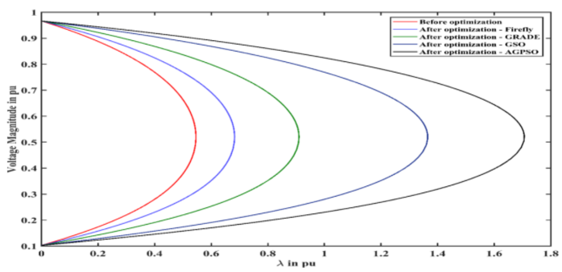


Figure 8. Comparison of λ V curves before and after optimization for Heavy loading condition for IEEE 30 bus system obtained using AGPSO algorithm

4.2 RESULTS ON IEEE-57 BUS SYSTEM

The AGPSO algorithm has been implemented to IEEE 57-bus system and the results are compared with that of Firefly,GRADE and GSO algorithm. The IEEE 57-bus network consists of 7 generators at buses 1,2,3,6,8,9,12, 4 transformers and 80 branches. The reactive power support is provided at the buses 18, 25 and 53.

The single line diagram of IEEE-57 bus system is presented in Figure 9. The system line data, bus data, generator data and the minimum and maximum limits for the control variables, the upper and lower limits of reactive power sources and transformer tap settings have been adopted from [30,31]. The total system active power demand is 12.508 p.u. and reactive power demand is 3.364 p.u. at 100 MVA base. The number of control variables considered for optimal reactive power dispatch in case of IEEE-57 bus system is 25. The control variables includes 7 generator bus voltage values(V_1,V_2,V_3,V_6,V_8,V_9,V_{12}) , 15 values of transformer tap position (T_1-T_{15}) and 3 injected reactive power values(Q_{C18}, Q_{C25} , Qc_{53}).

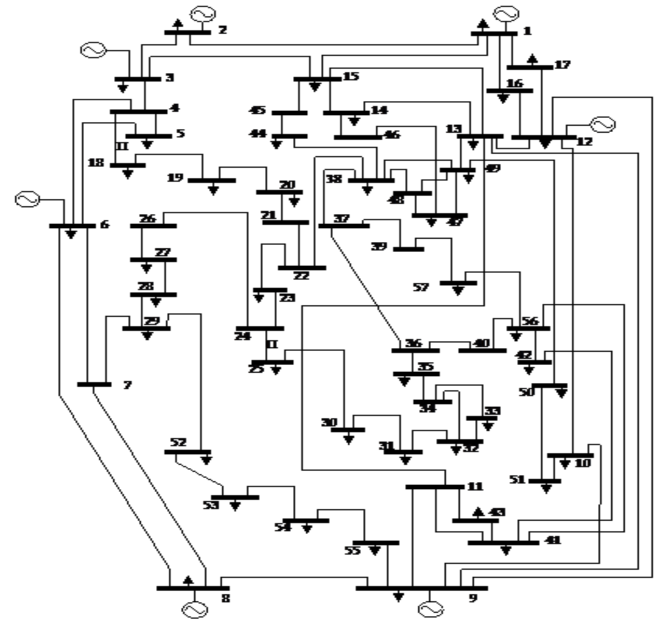


Fig 9 Single line diagram of IEEE 57 bus system

The voltage and tap settings limit is shown in Table 4. The reactive power generation limits for the IEEE 57-bus system are listed in Table 5.

Table 4. Limits for voltage and tap setting (in p.u.)

V_G^{max}	V_G^{min}	V_{load}^{max}	V_{load}^{min}	T_k^{max}	T_k^{min}
1.1	0.95	1.1	0.95	1.05	0.95

Table 5. Limits for reactive power generation

Bus no.	1	2	3	6	8	9	12
$Q_{g\,min}$(MVAR)	0	-40	-40	-40	-10	-6	-6
$Q_{g\,max}$(MVAR)	10	50	50	40	40	24	24

The AGPSO algorithm was executed for reactive power optimization problem using MATLAB 7 programming and is run for 30 trials each for different loading conditions in INTEL i5 processor to find out the best and worst results.

4.2.1 Comparison of Minimization of Real power losses

Light loaded condition

Under light loaded condition the load is reduced to about 625.40 MW (50% of the normal load) and the base case loss is obtained as 24.3750 MW.

Normal loaded condition

Under normal loaded condition the load is about 1250.80 MW and the base case loss is obtained as 27.8638 MW.

Heavy loaded condition

Under heavy loaded condition the load is about 1876.20 MW and the base case loss is obtained as 158.1204 MW. A comparison of fitness value and the real power loss obtained using Firefly GRADE,GSO and AGPSO algorithm under different loaded condition is shown in the Table 6 and Table 7 respectively.

Table 6. Comparison of fitness value for IEEE 57 bus system obtained using AGPSO Algorithm

	Light loaded condition				Normal loaded condition				Heavy loaded condition			
	GSO	AGPSO	GRADE	Firefly	GSO	AGPSO	GRADE	Firefly	GSO	AGPSO	GRADE	Firefly
fit	0.2701	0.2542	0.2797	0.42732	0.3362	0.3152	0.3359	1.093	2.0835	2.0421	2.0819	4.4924

Table 7. Comparison of real power loss for IEEE 57 bus system obtained using AGPSO Algorithm

Loading condition	Lightly loaded condition					Normal loaded condition					Heavily loaded condition				
Optimization Technique	Base case	Firefly	GRADE	GSO	AGPSO	Base Case	Firefly	GRADE	GSO	AGPSO	Base Case	Firefly	GRADE	GSO	AGPSO
P_{loss}(p.u)	0.24375	0.19762	0.18504	0.18154	0.17428	0.27863	0.25678	0.24369	0.24163	0.23546	1.5812	1.30134	1.28453	1.26854	1.25389

4.2.2 OPTIMUM SETTING OF CONTROL VARIABLE FOR IEEE 57 BUS SYSTEM

The optimal values of the control variables after optimization for different loading conditions are shown in Table 8.

4.2.3 COMPARISION OF IMPROVEMENT OF VOLTAGE PROFILE

The comparison of voltage levels before and after optimization for light loaded condition, normal loaded condition and heavy loaded condition is also presented in figures 10,11 and 12 respectively. The figure shows that the voltage profile has improved and is within the specified limits when compared to that of the base case voltage profile.

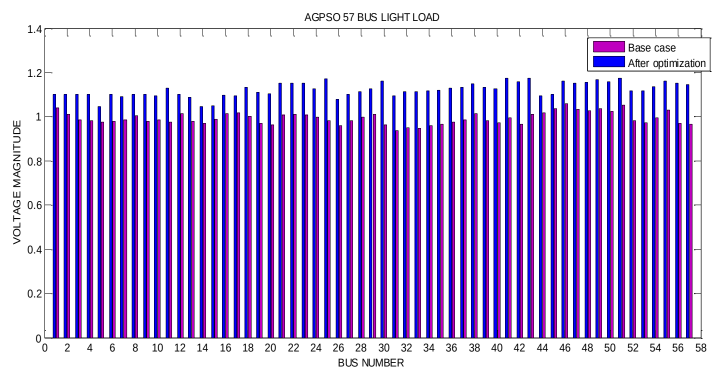


Figure 10. Comparison of voltage levels before and after optimization for light loading condition for IEEE 57 bus system obtained using AGPSO algorithm

Table 8. Optimal values of the control variables in p.u. obtained using AGPSO algorithm

Control variables	Light loaded condition	Normal loaded condition	Heavy loaded condition	Control variables	Light loaded condition	Normal loaded condition	Heavy loaded condition
V_1(p.u)	1.1	1.1	1.1	T_{24-26}	0.9605	0.9804	1.05
V_2(p.u)	1.1	1.1	1.1	T_{7-29}	1.05	1.0044	1.0011
V_3(p.u)	1.1	1.0999	1.1	T_{34-32}	0.9903	0.9724	1.05
V_6(p.u)	1.1	1.0978	1.1	T_{11-41}	0.9948	0.9587	0.9902
V_8(p.u)	1.1	1.0999	1.1	T_{15-45}	1.05	0.9554	0.95
V_9(p.u)	1.1	1.0961	1.093	T_{14-46}	1.05	0.9689	0.9976
V_{12}(p.u)	1.1	1.0999	1.1	T_{10-51}	1.05	0.9608	0.95
Q_{C18}(p.u)	0.04005	0.03773	0.20	T_{13-49}	1.0302	1.0157	1.0056
Q_{C25}(p.u)	0.07302	-0.0899	0.20	T_{11-43}	1.05	1.0412	0.95
Qc_{53}(p.u)	0.08218	-0.05260	0.20	T_{40-56}	1.05	0.9957	1.05
T_{4-18}	1.05	0.9734	0.95	T_{39-57}	1.05	0.9987	0.9857
T_{4-18}	1.05	1.0284	0.9686	T_{9-55}	1.05	1.0402	1.05
T_{21-20}	0.9541	1.0242	1.0442				

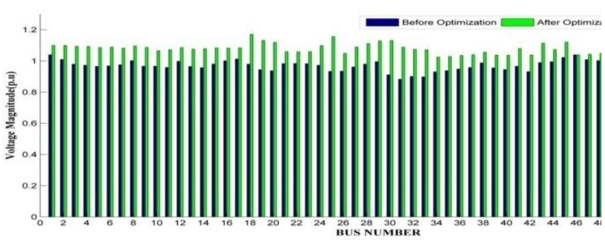


Figure 11. comparison of voltage levels before and after optimization for Normal loading condition for IEEE 57 bus system obtained using AGPSO algorithm

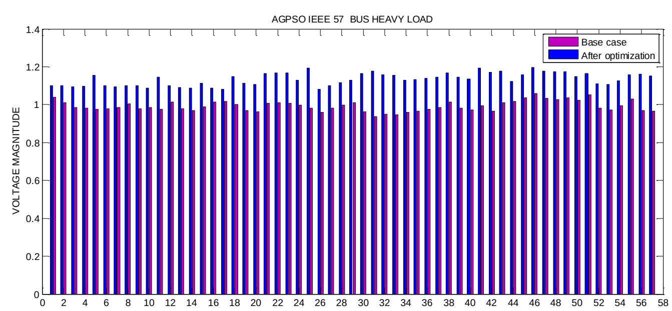


Figure 12. Comparison of voltage levels before and after optimization for Heavy loading condition for IEEE 57 bus system obtained using AGPSO algorithm

It is noted that in all the loading conditions all the control variables are within their specified limits after reactive power optimization using AGPSO Algorithm. The voltage profile has also improved after ORPD.

4.2.4 Comparision of Improvement in Loadability Margin

The λ-V curves obtained for IEEE 57 bus system for the three similar loading condition are presented below. In this case 31^{st} bus is found to be weak most bus by using sensitivity analysis. It is found that loadability margin is getting improved when AGPSO based optimization technique is employed to solve multi objective ORPD.

Light loaded condition

Under Light load condition the λ-V curves are as shown in figure 13 and the loadability margin has increased from 0.6077 (p.u) to 1.8991 p.u. when the system is optimized using AGPSO.

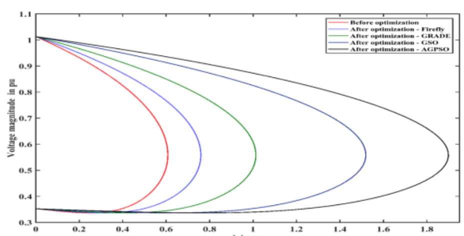


Figure 13. Comparison of λ V curves before and after optimization for light loading condition for IEEE 57 bus system obtained using AGPSO algorithm

Normal loaded condition

Figure 14 depicts the λ-V curves at 31^{st} bus of IEEE 57 bus system during normal load from the λ-V curves, it is observed that loadability margin has increased from 0.3568 (p.u) to 1.1150 (p.u). when the system is optimized using AGPSO technique.

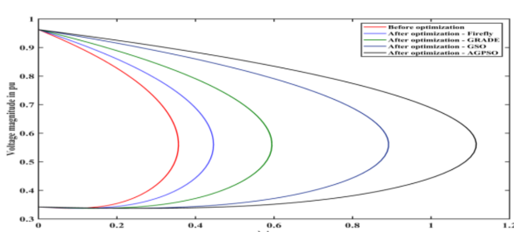


Figure 14: Comparison of λ V curves before and after optimization for normal loading condition for IEEE 57 bus system obtained using AGPSO algorithm

Heavy loaded condition

Under heavy load condition the curve is presented in figure 15 . Increases in loadability margin in this case is 0.4126 p.u which is the difference between 0.1942 (p.u before optimization and 0.6068 (p.u) after optimization

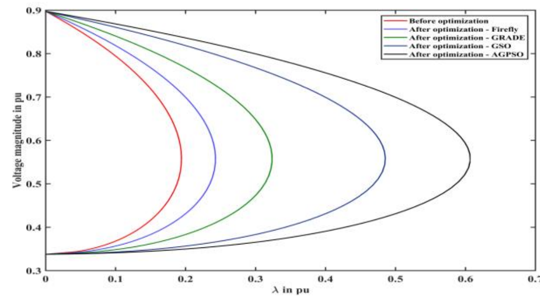


Figure 15. Comparison of λ V curves before and after optimization for heavy loading condition for IEEE 57 bus system obtained using AGPSO algorithm

Results obtained in all the cases presented in this thesis are compared with the result obtained using the existing method for standard test system. In all the cases the effectiveness of the algorithm is corraporated with the results already existing.

4.2.5 COMPARISON OF CONVERGENCE CHARACTERISTICS

A comparison of Convergence characteristics obtained using GRADE, GSO and AGPSO algorithm under different loading condition is shown in the figures 16,17 and 18 respectively.

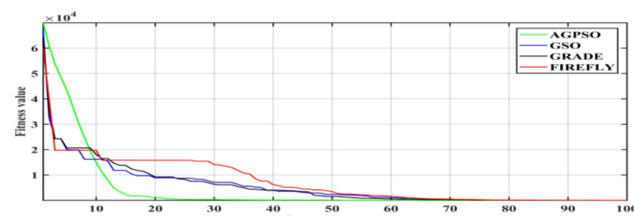


Figure 16. Comparison of convergence characteristics under Light loading Condition for IEEE 30 bus system

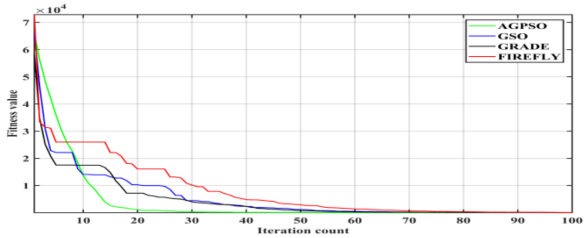


Figure 17. Comparison of convergence characteristics under Normal loading Condition for IEEE 30 bus system

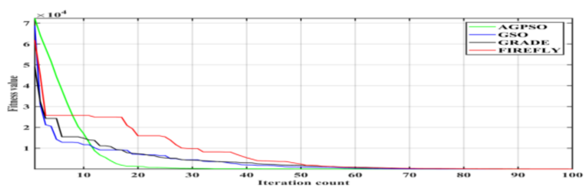


Figure 18. Comparison of convergence characteristics under Heavy loading Condition for IEEE 30 bus system

IEEE 57 bus system

A comparison of Convergence characteristics obtained using GRADE, GSO and AGPSO algorithm under different loading condition is shown in the figures 19,20 and 21 respectively.

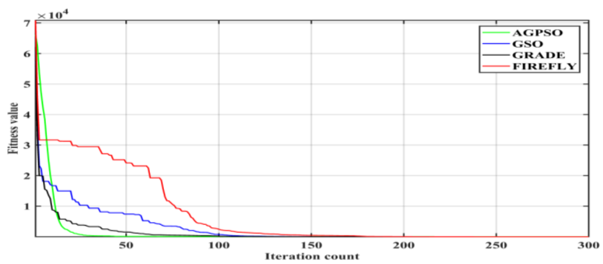


Figure 19. Comparison of convergence characteristics under Light loading Condition for IEEE 57 bus system

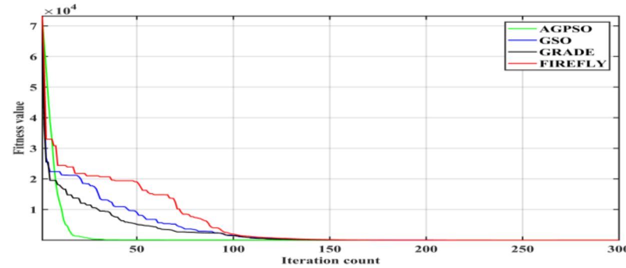


Figure 20. Comparison of convergence characteristics under Normal loading Condition for IEEE 57 bus system

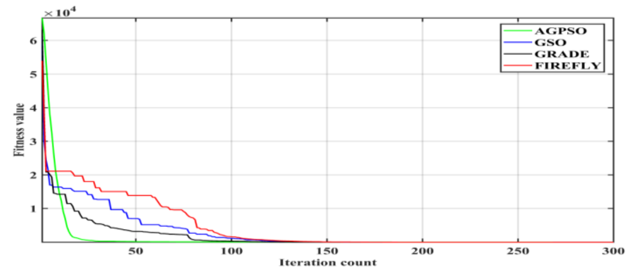


Figure 21. Comparison of convergence characteristics under Light loading Condition for IEEE 57 bus system

5. Conclusion

ORPD is performed in power system as a multi objective optimization problem subject to equality and inequality constraints. Latest optimization techniques such as firefly ,GRADE, GSO and AGPSO used to employed to solve multi objective optimization problem. Step by step procedure to solve ORPD is formulated in each case and algorithm is coded using M-coding in MATLAB platform. The ORPD problem stated through real power transmission line loss minimization and minimization of voltage deviation. Further attempt being made to increase the loadability margin of the network. The effectiveness of these Algorithm based approach, studies are performed in two test systems, viz, IEEE 30 bus system and IEEE 57-bus system under three loading conditions in all the cases.

The result obtained compare with the result already existing. It is observed that Firefly, GRADE,GSO and AGPSO based approach is capable of providing better performance with respect to real power loss minimization ,voltage profile improvement and increase the loadability margin. The effectiveness of the various algorithm used in this paper is also compared with already existing. It is observed that AGPSO based approach is capable of providing better result in all the cases considered with fastest convergence time and least number of iteration.

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