A NOVEL APPROCHES FOR SOLVING ORPD USING BIO-INSPIRED TECHNIQUES

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Abstract: *This paper presents Autonomous group Particle Swarm Optimization Algorithm(AGPSO), with dynamic weights, applied to reduce the real power loss in a system, improving the voltage profile and hence enhancing the performance of power system. Particle Swarm Optimization with detailed study on weights for particle movements is used. Control variables considered are Generator bus voltages, MVAR at capacitor banks, transformer tap settings and reactive power generation at generator buses. The optimal values of the control variables are obtained by solving the multi objective optimization problem using AGPSO Algorithm programmed using M coding in MATLAB platform. With the optimal setting for the control variables, Newton Rapson based power flow is performed for IEEE 30 bus system . Minimization of Real power loss ,improvement of voltage profile obtained and improvement in loadability margin are compared with the results obtained using 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 improves voltage profile and also minimizes the active power loss. The flow of reactive power in a power system can be controlled through generator voltages, transformer taps and switch-able VAR sources. A certain combination of these generator voltages, transformer tap positions and reactive power from capacitor banks result in optimized reactive power flow. The reactive power optimization problem is thus a nonlinear combinatorial optimization problem[22]. The search space is multidimensional due to large number of control variables. The complexity of reactive power optimization increases with increase in the size of power system.

Earlier, conventional methods were used for solving of reactive power flow optimization. These methods usually operate with single solution which is then optimized. The conventional methods have a major drawback of leading towards local minima. Also the conventional methods do not efficiently work for combination of variables. Time consumption of these methods is also very high. To overcome these drawbacks artificial intelligence methods[24] such as genetic algorithm [9,10,14], simulated annealing, Glow warm swarm [17], Particle Swarm Optimization[13], Biogeography based optimization and bare bone water cycle [1,3] methods have been used to solve reactive power optimization problem. Shanmugalatha etal. [16] have used optimization for voltage security and reactive power optimization, applied to different percentage of loads. Basu.M and Vardharajan [8,25] use differential evolution to find the optimized solution. Heuristic and Stochastic approach are implemented by Bhattacharya and Barun mandal [4,5] to find the optimal power flow solution. Particle Swarm Optimization has been applied for reactive power optimization by Altaf et al. [2], Barun mandal [6] and, Biplab Bhattacharyya [7]. Hybrid PSO having some additional features of other search methods [18,21] or some unique features applied to PSO have also been applied.PSO search technique has been studied separately to predict the optimized weights and factors for the search method [11,12]. Zhua et al. [27] uses fitness ratio to calculate the weights for particle movement in search space.The approach proposed in this paper uses Autonomous group Particle Swarm Optimization (AGPSO) technique with dynamic weights. The dynamic weights are so called, because their values change in each iteration as detailed in Section 3.3. A case is presented on IEEE 30 bus system and the final optimal variable values are shown.

2. Power Flow Equations

The power flow equations describe the constraints governing the flow of power in the power system. These equations or constraints can 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 Optimization (AGPSO) Algorithm is used. The inequality constraints are checked for violations during 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:

$$f_1 = \min \sum_{n=1}^{nl} P_{loss} \qquad (1)$$

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

$$f_2 = \sum_{i=1}^{n} \left| V_{max,spec} - v \right| \qquad (2)$$

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

$$f = \alpha(f_1) + \beta(f_2) \qquad (3)$$

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 - 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

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

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

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

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

$$V_{i,min} \le V_i \le V_{i,max} \qquad (6)$$

$i \epsilon N_B$ -Total number of buses

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

2.2.2.2 Generator Bus Reactive Power Constraint

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

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

2.2.2.3 Reactive Power Source Capacity Constraints

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

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

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

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) is a population-based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy [13] in 1995, inspired by social behavior of bird flocking or fish schooling. In PSO, each single solution is a "particle" in the search space. All of the particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called *gbest*. Throughout iterations, each particle adjusts its position and velocity as follows:

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

$$x_q^{t+1} = x_q^t + v_q^{t+1} \tag{11}$$

Where,

C_1 - Cognitive coefficient
C_2 - Social Factor
Rd - random number
W - inertial weight
x_q - position vector
v_q - velocity vector

3.2 Autonomous Group Particle Swarm Optimization Algorithm

In this paper, Std. PSO is modified by a mathematical model of distinct functions with diverse slopes, curvatures, and interception points are employed to tune social and cognitive constants of C_1 and C_2 parameters are given in Eq. (2) to generate particles of different behaviors to achieve the desired solution. This modification leads the Std. PSO into a modified standard particle swarm optimization algorithm named as Autonomous Groups Particle Swarm Optimization (AGPSO). AGPSO is mainly applied to alleviate the two major problems of trapping in local minima and slow convergence rate of std. PSO in tuning the parameters of reactive power equality and in equality constraints for a multi objective power system. Detailed description about AGPSO is available in [20] with the merits of AGPSO compared with variants of PSO. Updating strategies to tune the C_1 and C_2 parameters are given in Table. 1.

Method	Updating Formula C_1	Updating Formula C_2	Mathematical Functions
AGPSO 1			*Linear*
Group 1	$(-2.05/T)t + 2.55$	$(1/T)t+1.25$	
Group 2	$(-2.05/T)t + 2.55$	$(2t^3/T) + 0.5$	*Linear and Cubic*
Group 3	$(-2t^3/T^3) + 2.5$	$(1/T)t+1.25$	*Linear and Cubic*
Group 4	$(-2t^3/T^3) + 2.5$	$(2t^3/T^3) + 0.5$	*Cubic*
AGPSO 2			
Group 1	$2.5- (2\log(t) / \log(T))$	$(2\log(t)/\log(T))+0.5$	*Logarithmic*
Group 2	$(-2t^3/T^3) + 2.5$	$(2t^3/T^3) + 0.5$	*Cubic*
Group 3	$0.5+ 2 \exp[-(4t/T^2)]$	$2.2- 2 \exp[(4t/T^2)]$	*Exponential*
Group 4	$2.5+2(t/T)^2-2 (2t/T)$	$0.5-2(t/T)^2+2(2t/T)$	*Quadratic*
AGPSO 3			
Group 1	$1.95-2t^{1/3}/T^{1/3}$	$2t^{1/3}/T^{1/3} + 0.05$	*Principal third root*
Group 2	$(-2t^3/T^3) + 2.5$	$(2t^3/T^3) + 0.5$	*Cubic*
Group 3	$1.95-2t^{1/3}/T^{1/3}$	$(2t^3/T^3) + 0.5$	*Principal third root and Cubic*
Group 4	$(-2t^3/T^3) + 2.5$	$2t^{1/3}/T^{1/3}+ 0.05$	*Principal third root and Cubic*

where *t*- current iteration and *T*-total no of iterations

Table 1 Updating strategies with functions- C_1 and C_2

3.3 Dynamic weights

The particles in AGPSO [20]change their positions in every iteration based on individual best, global best and a random velocity. The new position of the particle is also dependent on the weights attached with these quantities. These weights can be static or dynamic. The static weights are determined by repeated execution of the algorithm and set before execution of the program. The dynamic weights change for each iteration of AGPSO. The weights introduced by Altaf et al. [2], make use of fitness ratio. The ratio is calculated separately for each control variable and the fitness values are taken from different particles. A novel concept is introduced here. The dynamic weights, used in this paper, change in every iteration, depending on the difference in fitness values of the particle and the referred best positions.

The new position of a particle is calculated as:

new position = old position + (difference between individual best position and current position)

(difference in losses of individual best position and current position)

scale value + (difference between global best position and current position)

(difference in losses of global best position and current position)

scale value + random value

sign is()

scale value

where scale value: to scale the calculated value in variable range.

signis : function which generates random positive or negative value.

Thus, more a particle is away from the global or individual best; the more it will be driven towards these positions. The introduction of dynamic weights makes the search converge faster. This method of calculation of weights was not found in the references mentioned

3.4 Merits of AGPSO Algorithm

AGPSO is a non-conventional optimization technique used for searching nonlinear multidimensional search spaces. The following are some of the advantages of using AGPSO:

(a) AGPSO's search includes multiple particles which reduces the chances of getting trapped in local minima.

(b) It is a stochastic search technique, which makes it suitable for searching vast unknown solution spaces.

(c) The problems faced by search techniques for non-differentiable objective equations are also overcome in PSO.

(d) AGPSO technique rules for changing particle position depends on individual as well as global best. Thus, the method normally does not get prematurely converged.

(e) AGPSO maintains the randomness in search during initialization of particle positions and also for change in particle position through random velocity.

3.5 Algorithm Steps for AGPSO Algorithm

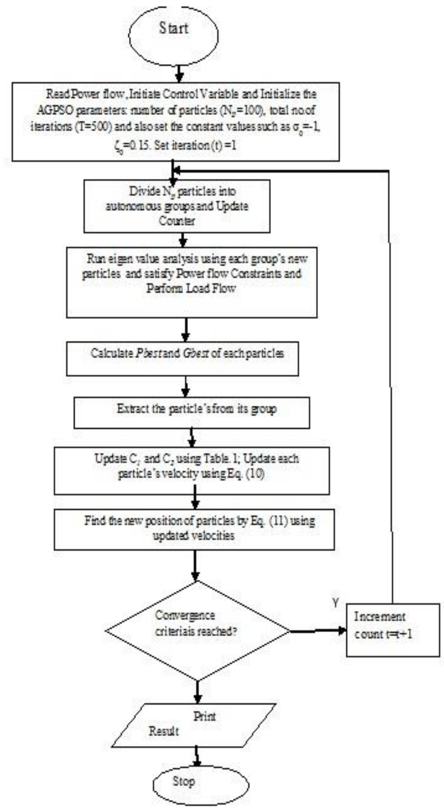

Fig 1. Flowchart of AGPSO algorithm for Multi Objective Optimization

Application of the AGPSO algorithm for the optimization of reactive power, parameters shown in Fig. 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.

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

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.

(ii) Load flow constraints are verified. Load flow is executed for each and every particle using fast decoupled method. This gives the active power loss, i.e., the value of objective function or the fitness value for each particle. Calculate *gbest*, *pbest*, and the fitness (Eq. (3)) of each particle x_i at each iteration

(iii) The individual best is updated for better fitness value of a particle.For each particle, the coefficients C1 and C2 are updated using its group's strategy from the table. 1.

(iv) Velocities $v_i$and positions of particles x_i will be updated using Eqs. (10) and (11). It should be noted that when the particle moves from the current position x_i to the new position x_{i+1} substituting (12) into Eq. (10) and Eq. (11), this results from the change in parameters of reactive power.

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

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

4 Results and Discussion

The effectiveness of AGPSO algorithm based optimization technique is tested in IEEE 30-bus and IEEE 57-bus test systems and the AGPSO 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). Continuation 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 transformerss 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 fig 2.

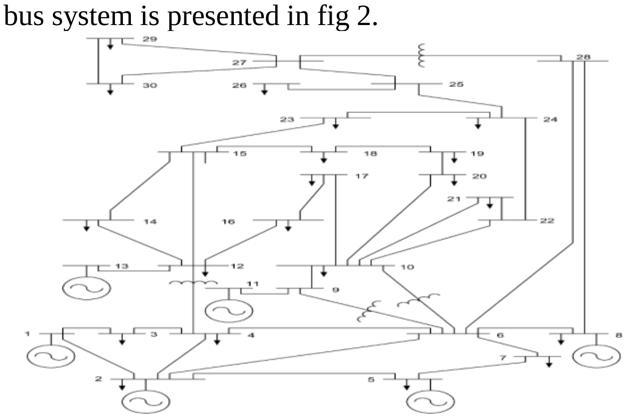

Fig 2. Single line diagram of IEEE 30 bus system

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_{6-9}, T_{6-10}, T_{4-12}, T_{27-28}) and 9 injected reactive power values (Q_{10}, Q_{12}, Q_{15}).

4.1.1 Comparision of Minimization of Real Power losses

Different loading conditions are considered for multi objective optimization. The normal loaded condition has a load of 2.834 p.u and two other loading conditions of which one is light loaded and the other heavy loaded when compared to that of the normal loaded condition are considered.

In light loaded condition, the load is reduced by 50% of the normal load in all load buses and in heavy loaded condition, the load is increased by 50% of the normal load in all load buses. Under light loaded condition the load is reduced to 1.4170 p.u and the base case loss is obtained as 0.037765 p.u. Under normal loaded condition the load is 2.834 p.u and the base case loss is obtained as 0.0566 p.u. Under heavily loaded condition the load is 4.2510 p.u and the base case loss is obtained as 0.4495 p.u. A comparison of fitness value for various loading condition is provided in Table II 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 III.

From Table III,it can be seen that, real power loss reduction is more when AGPSO algorithm is used compared to conventional techniques such as firefly[26], GSO[19] and GRADE. After 30 trials the real power losses obtained by ORPD using AGPSO algorithm is presented in Table III.

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 IV.

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_{6-9}	1.0003	0.97082	0.99
T_{6-10}	0.99	1.0157	0.99
T_{4-12}	0.99	0.95	0.9812
T_{28-27}	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

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

From Table IV, 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 given specified limits.

Table II 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

Table III 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

4.1.3COMPARISION 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.

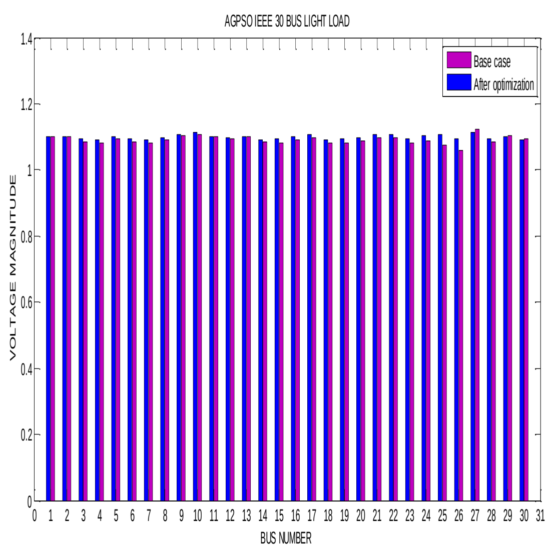

Fig 3: Comparison of voltage levels before and after optimization under light loaded condition for IEEE30 bus test system

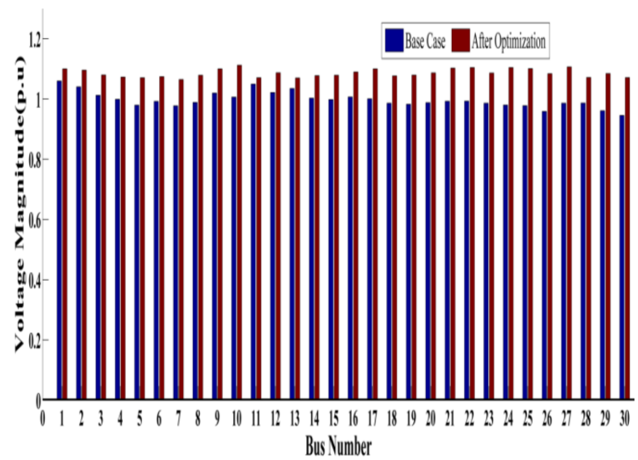

Fig 4: comparison of voltage levels before and after optimization under normal loaded condition for IEEE30 bus test system

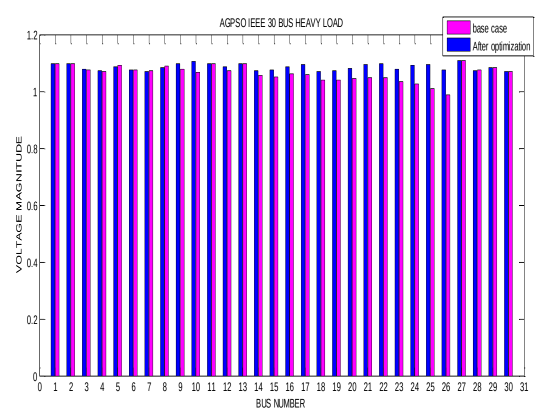

Fig 5: Comparison of voltage levels before and after optimization under heavy loaded condition for IEEE30 bus system

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[23] before and after optimization for different loading conditions is presented. As the 30^{th} 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 30^{th} 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).

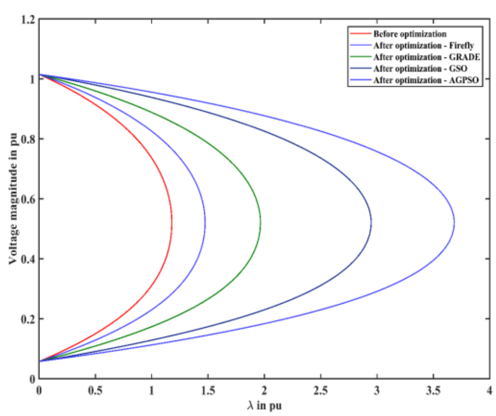

Fig 6: Comparison of λ V curves before and after optimization for light loading condition for IEEE 30 bus system obtained using AGPSO algorithm

Normal loaded condition

Figure 7 presents the λ-V curves at 30^{th} 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).

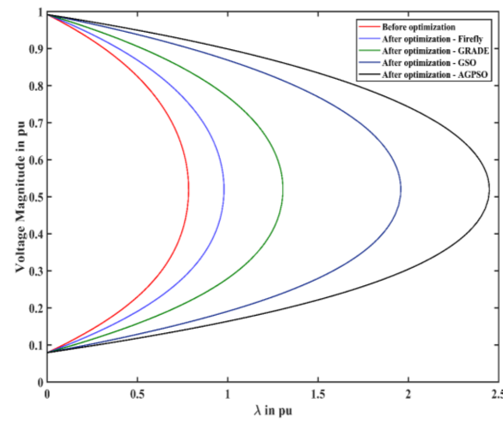

Fig 7: Comparison of λ V curves before and after optimization for normal loading condition for IEEE 30 bus system obtained using AGPSO algorithm

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.

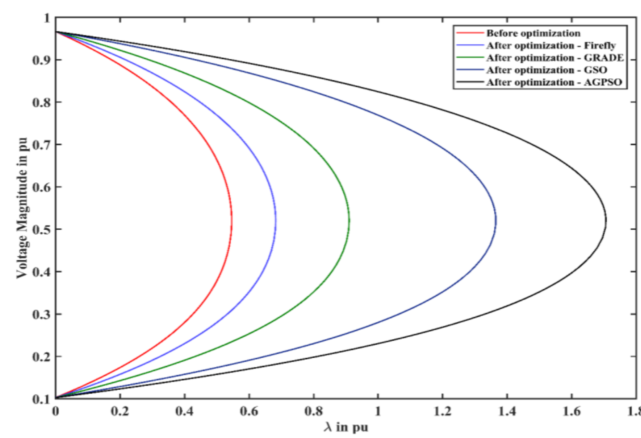

Fig 8: Comparison of λ V curves before and after optimization for Heavy loading condition for IEEE 30 bus system obtained using AGPSO algorithm

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.

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 IEEE 30 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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