PSO WITH TIME VARYING ACCELERATION COEFFICIENTS FOR SOLVING OPTIMAL POWER FLOW PROBLEM

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Abstract: *Optimal Power Flow (OPF) is a necessary implementation in power system operation. To resolve OPF problem Improved PSO with Time Varying Acceleration Coefficients (IPSO-TVAC) algorithm is utilized in this paper. The control variables applied are reactive power injections, generator real power outputs (except at the slack bus), transformer tap settings and generator voltages. Penalty parameter-less constraint handling scheme is used to handle the inequality constraints. The objective functions considered in this document are minimization of real power loss, voltage deviation, reactive power loss and total fuel cost. Standard IEEE 57-bus test system is employed to examine the proposed IPSO-TVAC and the outcomes are compared with other techniques reported in the literature. The results from the simulation show the effectiveness of the proposed method. Further, this proposed algorithm brings the system under optimal operation and as a consequence the system becomes secure.*

Key words: *Cost minimization, Particle Swarm Optimization (PSO), Optimal Power Flow (OPF), penalty parameter-less approach, Time Varying Acceleration Coefficients (TVAC).*

1. Introduction

In an electric power system operation and scheduling of OPF is an important tool. OPF was first introduced by Carpentier in 1962 [1]. OPF is a nonlinear multimodal optimization problem with non-smooth search space. By satisfying the inequality and equality constraints, optimization is achieved along with the optimal adjustment of control variables.

To determine the predicament of OPF [2-5] more than a few traditional systems are projected whereas they undergo few disadvantages such as non-differentiable objective functions, and fail to deal with systems having non-convex, and constraints. However, these algorithms are not able to handle mixed integer variables. To defeat the traditional methods of drawbacks, the optimization algorithms of heuristic have been designed to resolve the OPF problem. Because of their solution quality and convergence speed, those techniques have been used to solve OPF problems successfully [6-18]. However, these algorithms are not used to handle the mixed integer variables because the OPF control variables consist of both discrete and continuous variables [6].However, continuous variables are used for injection of reactive power and tap setting of transformer of shunt devices instead of practical discrete values [6]. PSO technique has the agility to develop both local and global exploration abilities [7].

PSO algorithm introduced by Eberhart and Kennedy [19] is a population based stochastic optimization technique and is motivated by the behaviour of organisms such as fish schooling and bird flocking. In recent years, PSO algorithm has been effectively used to resolve optimization problems in reactive power optimization, optimal placement of multiple distributed generator units, relieving transmission congestion, transmission expansion planning and so on. It is experimental that the conventional PSO suffer from premature convergence [15]. Relative tuning of social and cognitive components play an important role in the solution quality of PSO [15]. Time varying acceleration coefficients (TVAC) structure leads to a proper balance between the social and cognitive and components in the initial phase and latter iterations [15]. To stay away from local optimum trapping and to enhance the quality of the solution an Improved PSO (IPSO) is utilized [16].

In this paper Mixed-integer OPF difficulties subject to a set of inequality and equality constraints are solved by using IPSO-TVAC approach. Penalty parameter-less constraint handling scheme is used to handle the inequality constraints, while mixed integer handling method is used to handle OPF control variables. Minimization of real power loss, total fuel cost, voltage deviation and reactive power loss are considered as the objective function. The standard IEEE 57-bus system is taken as a model to test the effectiveness of proposed method. The results from the simulation provide an optimal solution of OPF problem.

The order of the paper is: Section 2 represents the OPF problem formulation and the incorporation of constraints in OPF. Section 3 explains the overview of PSO algorithm, treatment of mixed integer variables and the implementation of the proposed IPSO-TVAC algorithm for solving the OPF problem. Section 4 represents the comparison of simulation results obtained by the proposed algorithm in IEEE 57-bus systems with other algorithms in literature. Finally, the conclusions are drawn in the Fifth section.

2. Problem Formulation

The OPF problem is formulated as a mixed integer nonlinear optimization problem. Generator voltages V_G, generator real power outputs P_G except at the slack bus, reactive power injections Q_C and transformer tap settings T are the control variables. The dependent variables include slack bus active power P_{G1}, load bus voltages V_L, reactive powers of generators Q_G and thermal limit of transmission lines S_L. The equality constraints consist of power flow equations. The inequality constraints include the constraints on control and dependent variables. The continuous variables are generator voltages and generator real power outputs except at the slack bus and discrete variables are reactive power injections of the shunt compensators and transformer tap settings.

2.1. Objective function

2.1.1. Minimization of total fuel cost

The fuel cost total F_T (\$/hr) of generating units N_G can be stated as:

$$F_T = \sum_{i=1}^{N_G} a_i P_{G_i}^2 + b_i P_{G_i} + c_i \quad (1)$$

The fuel cost coefficients of the i^{th} generating units are a_i, b_i and c_i and the real power output of the i^{th} generating unit is P_{G_i}.

2.2. Constraints

The real and reactive power flow equations stand for equality constraints. The system operational and security limits are inequality constraints and are specified as follows.

$$V_{G_i}^{min} \le V_{G_i} \le V_{G_i}^{max}, \ \ i = 1, \dots, N_G \quad (2)$$

$$P_{G_i}^{min} \le P_{G_i} \le P_{G_i}^{max}, \ \ i = 1, \dots, N_G \quad (3)$$

$$Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max}, \ \ i = 1, \dots, N_G \quad (4)$$

$$T_i^{min} \le T_i \le T_i^{max}, \ \ i = 1, \dots, N_T \quad (5)$$

$$Q_{C_i}^{min} \le Q_{C_i} \le Q_{C_i}^{max}, \ \ i = 1, \dots, N_C \quad (6)$$

$$V_{L_i}^{min} \le V_{L_i} \le V_{L_i}^{max}, \ \ i = 1, \dots, N_{PQ} \quad (7)$$

$$S_{L_i} \le S_{L_i}^{max}, \ \ i = 1, \dots, N_L \quad (8)$$

Where N_T is the number of regulating transformers, N_{PQ} is the number of load buses, N_C is number of VAR compensators and N_G is number of generator buses.

2.3. Incorporation of constraints

Newton Raphson (NR) load flow solution assures the equality constraints. Hence, there is no need to handle them using any constraint handling method.

Penalty function method is the most commonly used constraint handling method to handle the inequality constraints. The inequality constraints include the constraints on both the control and the dependent variables (u, x).

The control variables are randomly generated during the IPSO-TVAC algorithm process. If these variables are not generated within the feasible range, they are fixed to their respective upper or lower limit and it is calculated as

$$u_i = \begin{cases} u_i^{max} & if\ u_i > u_i^{max} \\ u_i^{min} & if\ u_i < u_i^{min} \end{cases} \quad (9)$$

Therefore, in the proposed method the inequality constraints of the control variables are always satisfied.

Hence, the inequality constraints of the dependent variables are controlled by using penalty parameter less constraint handling scheme [18]. These constraints are incorporated by changing the objective function and it is given as

$$F = \begin{cases} F_T & if\ x\ is\ feasible \\ f_{max} + CV & otherwise \end{cases} \quad (10)$$

Where f_{max} is the objective function value of the worst feasible solution in the population and CV is the overall constraint violation and it is given by

$$CV = max(0, P_{G,slack} - P_{G,slack}^{max}, P_{G,slack}^{min} - P_{G,slack}) + \sum_{i=1}^{N_{PQ}} max(0, V_i - V_i^{max}, V_i^{min} - V_i) + \sum_{i=1}^{N_G} max(0, Q_{Gi} - Q_{Gi}^{max}, Q_{Gi}^{min} - Q_{Gi}) + \sum_{i=1}^{N_L} max(|S_l| - S_l^{max}) \quad (11)$$

In a feasible solution, there is no constraint violation and F is simply the objective function F_T itself. In an infeasible solution, there will be constraint violations and F is the sum of CV and f_{max}.

2.4. Severity index

Contingency analysis is used to find AC power flow solution in reactive, active power flows and magnitudes of bus voltage. Line outage is considered, while ranking the contingency based on performance index x. In order to alert and evaluate the system operators concerned the critical contingencies, severity index examination is done. As various probable outages create a contingency set, out of which some cases may lead to congestion problems. Corrective measures should be promptly made on those critical contingency. The process of recognizing the N-1 criterion is submitted as contingency choice and it is positioned in the order of its apparent power performance index (PI) rate, it is expressed as

$$PI = \sum_{i=1}^{N_l} \left(\frac{Sflow_i}{Smax_i}\right)^2 \quad (12)$$

Where PI is the apparent power flow Performance Index, $Sflow_i$ is the apparent power flow in i^{th} line, $Smax_i$ is the maximum apparent power flow in i^{th} line and N_l is the total number of lines.

3. Overview of Partical Swarm Optimization

3.1 Conventional PSO

Kennedy and Eberhart introduced PSO algorithm, is a population-based stochastic optimization technique. In PSO, each particle can be represented by its position and velocity. In a multidimensional search space particles alter their positions by moving around until a relatively unchanged position has been attained. In the search space, global best is the best position encountered so far among the whole population and is denoted as Gbest, whereas best position encountered in the individual particle is Pbest. The updated velocity and position of each particle is formulated as follows.

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

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

where k is the current iteration, $V_{j,d}^k$ 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, c1 is cognitive component acceleration coefficients and c2 is social component acceleration coefficients, rand1 and rand2 are the random numbers involving 0 and 1 and they are uniformly distributed, $X_{j,d}^k$ j,d,k shows the position of particle , dimension and iteration. C is the constriction factor and w is the inertia weight is calculated as follows

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

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

Where $\phi = 4.1$, the initial and final values of inertia weight are W_{max} and W_{min} respectively. Inertia weight is linearly decreasing as the generations progressed and is updated. The current generation is G and the maximum number of generation is G_{max} .

To supervise the redundant traveling of particles, the velocity of each particle is attained by using (13), it is restricted by their upper and lower limits and it can be specified by

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

Where $V_d^{max}$the velocity is maximum, V_d^{min} is the velocity minimum in the d^th^ dimension and expressed by

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

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

Where K=5 is the limit to manage the number of space in the d^{th} dimension [6].

Even though with a fast convergence rate the algorithm of PSO can decide an enhanced solution, its capability to fine adjustment of optimal solution lacks because of diversity at the end of the search.

3.2. IPSO-TVAC

In order to prevent premature convergence, the proposed IPSO-TVAC algorithm is employed in crossover operator and time varying acceleration coefficients to enhance particle diversity and improve the global searching capability. The position of particle j obtained in (13) is mixed with Pbest to generate the new position is shown by

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

Where C_r is the crossover probability. In the conventional PSO algorithm, c_1 and c_2 are fixed as 2.0. Comparatively the social component c_2 is high value in assessment with cognitive component c_1 which leads particles to trap into local optimum. Relatively high value of cognitive component makes the particles to wander in the region of the search space. The following equations are used to obtain solution quality and also represent the updated acceleration coefficients.

$$c_1 = (c_{1f} - c_{1i}) + \left(\frac{G}{G_{max}}\right) * c_{1i} \quad (21)$$

$$c_2 = (c_{2f} - c_{2i}) + \left(\frac{G}{G_{max}}\right) * c_{2i} \quad (22)$$

Where c_{1i} and c_{2i} are the initial values of c_1 and c_2, c_{1f} and c_{2f} are the final values of c_1 and c_2. Local search space is reduced as c_1 decreases and c_2 increases to accelerate the solution towards the global convergence.

3.3. Mixed integer handling method

The discrete and continuous variables are the control variables but the proposed IPSO-TVAC algorithm can handle continuous variables only. In the initialization process, all the individuals in the population are generated randomly within the feasible range. During initialization, the continuous variables of an individual are generated randomly using (23), while the discrete variables are generated randomly using (24). Thus, the initial populations hold the control variables for such as real power outputs of the generator (except slack bus), continuous form of generator voltages, tap setting of the transformer and reactive power injections of shunt compensators in discrete form. However, the proposed algorithm can generate only continuous control variables by updating the velocity and position using (13) and (14).While evaluating the fitness function, the values obtained for the discrete variables using the proposed algorithm are rounded to their nearest discrete values using (25).

$$x_{cv} = rand * (var\ high - var\ low) + var\ low \quad (23)$$

$$x_{dv} = min + n_k * \Delta s \quad (24)$$

$$x_{dv,d} = round\left(\frac{x_{dv,d}}{\Delta s}\right) * \Delta s \quad (25)$$

Where x_{cv} and x_{dv} represent the continuous and discrete control variables, high and low are the maximum and minimum values of x_{cv}, min is the minimum value for x_{dv}, nk is the number of positions, Δs is the step size and $x_{dv,d}$ represents the discrete control variable at d^{th} dimension.

3.4. Implementation of IPSO-TVAC for OPF problem

The flowchart for solving OPF problem is depicted in Fig.1. The steps involved in solving OPF problem using the IPSO-TVAC algorithm are summarized as follows:

1. Define the parameters required for the algorithm and the feasible range for the control and dependent variables.
2. Randomly generate the initial population using (23 and 24).
3. Run N-R power flow and evaluate fitness function for each particle in the population using (10).
4. Repeat step 3 for the entire particles in the population until the fitness function is evaluated.
5. The estimation of fitness value is represented in (10) and it is the initial Pbest values. Gbest is the best value surrounded by all the Pbest values
6. Set the maximum number of generations and set generation count=1.
7. Update the velocity using (13) and apply velocity limits using (17).
8. Update the position using (14) and perform crossover via (20).
9. Clamp the control variables into the feasible range by using (9), if the inequality constraints of the control variables are violated; else go to step 10.
10. Run N-R power flow and evaluate fitness function for each updated particle by using (10).
11. Adjust Pbest and Gbest. Based on the following situation, Pbest is revised
    - When two feasible solutions are compared, the one with better objective function value is chosen.
    - When a feasible and an infeasible solution are compared, the feasible solution is chosen.
    - When two infeasible solutions are compared, the one with smaller constraint violation is chosen.
12. Increase the generation count.
13. Repeat step 7 to step 12 until the maximum generation is reached.

4. 0. Results obtained from simulation

The projected IPSO-TVAC algorithm is tested in IEEE 57-bus systems. All Simulation studies are performed by MATLAB programs and the power flow calculation is performed by Newton-Rapshon method using MATPOWER software package version 4.0b4 [20]. In MATPOWER, the procedure used to explain the OPF problem is interior point method. The parameter settings for the IPSO-TVAC algorithm are shown in Table 1.

4.1 IEEE-57 Bus systems

The IEEE 57-bus system consists of 80 lines, 7 generators, 17 tap setting transformers and 3 shunt VAR compensators. The total active and reactive power demands of the system are 1250.8

MW and 336.4 MVAR, respectively. The system data is taken from [20]. The voltage magnitude limits of the generator buses and load buses are between 0.95 - 1.1 p.u. and 0.94 - 1.06 p.u., respectively. The transformer tap settings have 20 discrete steps of 0.01p.u and can be varied in the range 0.9 -1.1p.u. The shunt compensators have 20 discrete steps of 0.01 p.u. and can be varied in the range of 0 - 0.03 p.u. The cases considered are as follows.
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Table 1 Parameter settings for IPSO-TVAC

Parameter	Setting
W	0.9
W_{min}	0.4
c_{1i}, c_{2f}	2.5
c_{1f}, c_{2i}	0.2
C_r	0.6
No. of iterations	200
Trial runs	20
Population size	165

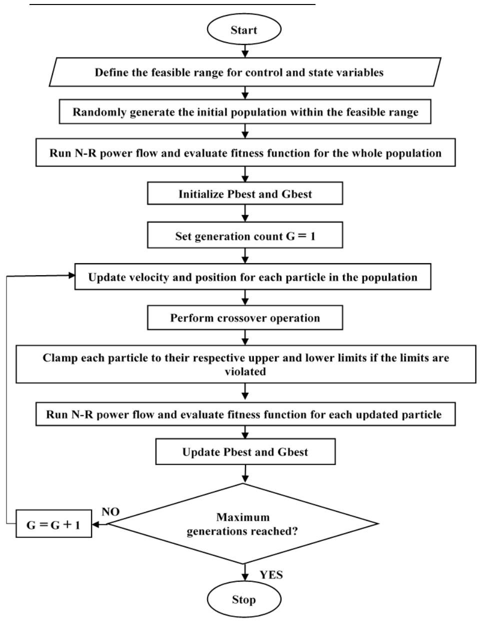

Fig. 1 Flowchart for IPSO-TVAC algorithm

4.1.1. Case 1- Fuel cost minimization

In this case, the generator cost curves are modeled by quadratic functions as defined in (1). The total active power is 1250.8 MW and the reactive power demand of the system is 336.4 MVAR. The system data's are taken from [20]. The IPSO-TVAC algorithm in 20 independent trail runs, generate a minimum fuel cost of 41669.14 $/hr with an average of 41681.74 $/hr and a maximum of 41716.65 $/hr. Table 2 shows the comparison of results obtained for different cases in IEEE 57-bus system. It is clear that the minimum cost obtained using the proposed method is less than the cost obtained by the heuristic algorithms [6 & 8] reported in literature and also the cost obtained by MATPOWER. Though, the best solution obtained using GSA algorithm is an infeasible solution since there are voltage magnitude violations at the load buses 18, 19, 20, 26, 27, 28, 29, 30, 31, 32, 33, 42, 51, 56, and 57.Compared to other algorithm this approach gives better solution quality and usefulness. The convergence characteristics corresponding to the minimum fuel cost is shown in Fig.2. Table 3 presents the arithmetical results obtained for case 1 for 20 independent trial runs. From Table 3, it is clear that the proposed algorithm gives enhanced outcome for large systems.

Table 2 Comparison of the results obtained for case 1

Method	F_T ($/hr)
IPSO-TVAC	**41669.14**
GSA [6]	41695.8717[a]
ABC [8]	41693.9
Matpower OPF	41737.79

[a] *Infeasible solution*

Table 3 Arithmetical results obtained for 20 trial runs for case 1

Method	Fuel cost ($/hr)		
	Minimum	Average	Maximum
IPSO-TVAC	41669.14	41681.74	41716.65
ABC	41693.9589	41778.6732	41867.8528

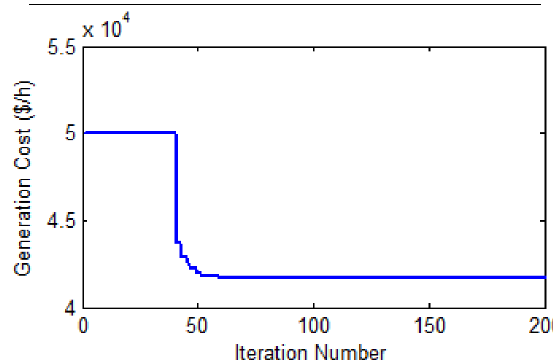

Fig. 2. Convergence characteristics for fuel cost Minimization

4.1.2 Case 2 Minimization of fuel cost during contingency condition

In this case, the most critical contingency state is simulated by opening the line 1-2 [12]. Table 4 represents the optimum settings of control variables for fuel cost minimization of case 1 and case 2. From the Table 4 it is clear that better result is obtained using the proposed IPSO-TVAC algorithm when compared to the result obtained by Interior point algorithm using Matpower software package 4.0. During the contingency case, the minimum fuel cost obtained using the proposed IPSO-TVAC approach is 41746.59 $/hr with an average of 43638.64 $/h and maximum of 41767.53 $/hr.

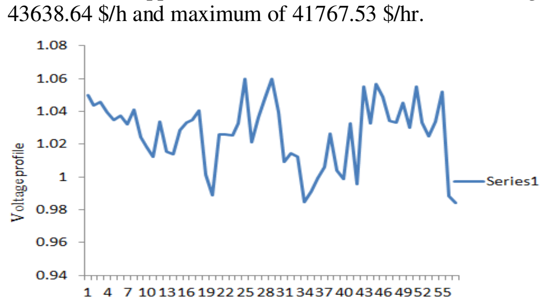

Fig.3 Voltage profile improvement for real power loss

4.1.3 Case 3: Voltage profile improvement

Maintaining the load bus voltages within the specified limit is a major operating task in power system. In this case, the load bus voltage deviations are minimized to 1.0 p.u. as defined in (2). Contingency occurs by opening the line 1-2 for this system.

The optimum settings of control variables corresponding to voltage profile improvement is presented in Table 5. It is clear from Table 5 that the proposed method yields improved results compare to the other methods. The voltage profile improvement for real power loss is depicted in Fig.3. The results obtained are in feasible range and most of the load buses are concentrated at 1.0 p.u.

Table 4 Optimal setting of control variables for fuel cost minimization

Control Variables	IPSO – TVAC		GSA(6)	EADPSO(13)	EADPSO(13)	EADPSO(13)	ABC(8)
	Case 1	Case 2	Case 1	Case 1	Case 2	Case 3	Case 1
P_{G2}(p.u)	0.810138	0.605762	0.9263	0.7512	0.8892	0.6828	0.900328
P_{G3}(p.u)	0.445117	0.453797	0.45318	0.4404	0.424	0.4774	0.445147
P_{G6}(p.u)	0.786705	0.759943	0.72355	0.9534	0.6768	0.3453	0.742003
P_{G8}(p.u)	4.6179	4.641956	4.64743	4.5535	4.6793	4.8363	4.548475
P_{G9}(p.u)	1	1	0.84999	0.9302	0.7844	0.8136	0.968847
P_{G12}(p.u)	3.576311	3.71906	3.63951	3.5929	3.7959	3.8754	3.627722
V_{G1}(p.u)	1.0613	1.0385	1.05941	1.0696	1.056	1.0145	1.0423
V_{G2}(p.u)	1.0577	1.0209	1.05759	1.0671	1.0496	1.0081	1.0411
V_{G3}(p.u)	1.0523	1.0338	1.06	1.0612	1.029	1.0006	1.0385
V_{G6}(p.u)	1.0566	1.0422	1.06	1.0624	1.0255	1.0408	1.0549
V_{G8}(p.u)	1.067	1.0573	1.05999	1.0681	1.0141	1.0892	1.064
V_{G9}(p.u)	1.046	1.0299	1.05999	1.0433	0.9969	1.037	1.0369
V_{G12}(p.u)	1.0541	1.0286	1.0459	1.0411	1.0094	1.0046	1.0406
T_{19}(p.u)	1	1.01	0.9	1.0995	1.0635	0.9016	0.9375
T_{20}(p.u)	1.01	1.01	0.9	1.0999	0.9463	1.029	1.05
T_{31}(p.u)	0.94	1	0.90856	1.0973	0.9408	0.9877	0.975
T_{35}(p.u)	1.01	1.01	1.05921	1.0575	1.0997	0.9054	0.95
T_{36}(p.u)	1.02	1.1	0.99921	0.9382	1.0483	1.0952	1.0125
T_{37}(p.u)	1.08	0.99	0.92201	1.0329	0.9761	1.0141	1
T_{41}(p.u)	1.03	0.99	0.93243	0.9987	0.9734	1.0296	1.0125
T_{46}(p.u)	1.02	0.98	1.08828	0.9651	0.9	0.9251	0.9125
T_{54}(p.u)	0.9	1.03	1.03902	0.9358	0.9028	0.9036	0.9
T_{58}(p.u)	0.99	0.99	1.04318	0.9852	0.9546	0.9477	1.0125
T_{59}(p.u)	1.02	0.98	1.02494	0.9692	0.9321	0.9605	0.9875
T_{65}(p.u)	1.01	1	0.95425	0.9678	0.9383	1.0058	1
T_{66}(p.u)	1	0.98	0.92897	0.9434	0.9146	0.9013	0.9625
T_{71}(p.u)	1.04	0.97	1.09942	0.9845	0.9986	0.998	0.9625
T_{73}(p.u)	1.05	1	0.96948	1.0041	1.0706	0.9218	0.9625
T_{76}(p.u)	0.97	0.97	1.062	0.9819	0.9346	0.9655	0.925
T_{80}(p.u)	1.06	0.99	1.09388	1.0299	0.9644	1.0474	0.9875
Q_{C18}(p.u)	0.13	0.16	0.15243	0.2966	0.2116	0.0072	0.16
Q_{C25}(p.u)	0.18	0.2	0.14403	0.1161	0.2543	0.1489	0.15
Q_{C53}(p.u)	0.18	0.15	0.15102	0.1231	0.3	0.2104	0.14
P_{G1}(p.u)	1.433932	1.492857	1.42369	1.4413	1.4316	1.6442	1.428106
Fuel cost($/hr)	**41669.14**	**41767.53**	41695.87	41,697.54	41,802.78	41,867.68	41693.959

Matpower cost($/hr)	41737.79	41801.31					
Vdev(p.u)	1.3818	2.0319	-	1.3466	1.4516	0.7483	-
Ploss(p.u)	0.162103	0.198486	-	0.1549	0.1732	0.167	-

Case 1-without lineoutage, Case 2-with lineoutage

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Table 5 Voltage profile improvement for all cases

	Fuel Cost Minimization		Voltage Deviation	Real Power Loss Minimization		Reactive Power Loss Minimization	
Bus No	Case 1	Case 2	Case 2	Case 1	Case 2	Case 1	Case 2
1	1.0613	1.0769	1.047	1.0501	1.0551	1.0546	1.0391
2	1.0577	1.0769	1.0714	1.0436	1.0483	1.0444	1.0199
3	1.0523	1.0769	1.0237	1.0458	1.0496	1.0467	1.0391
4	1.0519	1.0601	1.9588	1.0397	1.0407	1.0475	1.0349
5	1.0516	1.0681	0.2229	1.0347	1.0393	1.0469	1.0409
6	1.0566	1.0769	0.9945	1.0373	1.0438	1.0517	1.0489
7	1.0524	1.0635	0.488	1.0321	1.0388	1.0447	1.0474
8	1.067	1.0769	1.0009	1.041	1.0444	1.0565	1.0651
9	1.046	1.0769	0.984	1.0242	1.0291	1.0381	1.04
10	1.0376	1.0556	235.849	1.0186	1.0224	1.0306	1.0303
11	1.0312	1.0629	84.694	1.0124	1.0169	1.0267	1.0244
12	1.0541	1.0769	0.993	1.0339	1.0386	1.0528	1.0504
13	1.0357	1.066	130	1.0155	1.02	1.031	1.0276
14	1.0319	1.0635	255.891	1.014	1.0173	1.0167	1.0195
15	1.0411	1.0637	323.64	1.0288	1.0323	1.0326	1.0247
16	1.0509	1.0722	65.6128	1.0331	1.0377	1.0431	1.0374
17	1.0495	1.0684	76.0095	1.0347	1.0394	1.039	1.0287
18	1.0547	1.042	5.7011	1.0408	1.0268	1.0257	1.0471
19	1.0367	0.9682	17.9153	1.0012	0.9969	0.9935	0.9871
20	1.0375	0.9348	26.5993	0.9889	0.9902	0.9861	0.9616
21	0.9893	0.9975	35.2139	1.0261	1.0222	1.0041	0.9886
22	0.9925	0.9922	18.6489	1.0257	1.0234	1.0052	0.9851
23	0.993	0.9932	18.2212	1.0253	1.0225	1.0051	0.985
24	1.016	1.0236	0.943	1.0328	1.0221	1.0199	0.9979
25	1.0436	1.0335	1.0069	1.06	1.0573	1.0488	1.0194
26	0.9409	0.9776	2.5421	1.0215	1.022	0.9821	0.9795
27	0.9768	1.0356	1.2549	1.0364	1.0359	1.0144	1.0004
28	0.9974	1.0642	1.379	1.0484	1.0473	1.033	1.0146
29	1.015	1.0865	0.5701	1.06	1.0583	1.0487	1.0274
30	1.0153	1.0044	2.3036	1.0395	1.037	1.0228	0.9974
31	0.9667	0.954	4.7604	1.0094	1.0075	0.9797	0.9644
32	0.9455	0.9307	0.124	1.0144	1.0134	0.9662	0.9673
33	0.9432	0.9284	0.0829	1.0122	1.0112	0.9639	0.9651
34	0.964	0.959	0.1648	0.9849	0.984	0.9717	0.947
35	0.9671	0.962	1.1354	0.9908	0.9899	0.9757	0.9529

36	0.974	0.9687	0.5109	0.9994	0.9987	0.983	0.9619
37	0.978	0.9736	0.1136	1.0059	1.0051	0.9885	0.9671
38	0.9924	0.9891	1.6193	1.0264	1.0254	1.0054	0.9846
39	0.9759	0.9722	0.0023	1.004	1.0033	0.987	0.9651
40	0.9749	0.9683	1.1091	0.9988	0.9982	0.9825	0.9631
41	1.0168	0.9936	39.0531	1.0328	1.0563	1.0194	1.016
42	0.973	0.9513	10.6552	0.9955	1.0192	0.9793	0.9713
43	0.9967	0.9849	71.1614	1.0552	1.057	1.0463	1.0205
44	1.0039	1.0109	32.2655	1.0329	1.033	1.0152	1.002
45	1.0384	1.0669	200.703	1.0566	1.0596	1.047	1.0507
46	1.0064	0.9738	7.9735	1.0491	1.0515	1.0564	0.9961
47	0.9937	0.9744	11.7859	1.0342	1.035	1.0228	0.9839
48	0.9939	0.9801	0.5482	1.033	1.0329	1.0144	0.9836
49	0.9995	0.9869	46.5233	1.0452	1.0436	0.9944	0.9817
50	0.9874	0.9912	102.792	1.0301	1.0302	0.9839	0.9717
51	1.0198	1.0516	191.552	1.0551	1.058	1.0191	1.0085
52	0.9855	1.0554	1.9005	1.0332	1.0429	1.0172	0.9879
53	0.9764	1.0452	1.8991	1.0251	1.0408	1.0071	0.9733
54	0.9759	1.0275	0.9184	1.0338	1.0411	0.9822	0.9602
55	0.9859	1.0206	1.0655	1.0519	1.0514	0.9691	0.9585
56	0.9603	0.941	0.92208	0.9886	1.0118	0.9702	0.9578
57	0.9563	0.9329	0.1435	0.9843	1.0073	0.9628	0.9536

4.1.4 Case 4 - Minimization of voltage deviation

In power system, the harms of rise in load demand are rectified by maintaining the bus voltage constantly. The voltage deviation is needed in order to avoid the voltage profile to move towards the maximum. Voltage Deviation (VD) is defined as

$$VD = \sum_{K=1}^{n\,bus} |V_k - V_{dk}| \quad (26)$$

Where V_k = Voltage magnitude of bus k, V_{dk} = desired voltage magnitude of bus k usually equals 1.0 p.u, n bus = No of buses. The cost obtained from voltage deviation for without contingency is 48009.788 $/hr, for with contingency is 44572.16 $/hr. Fig.4 illustrates the convergence characteristic of voltage deviation.

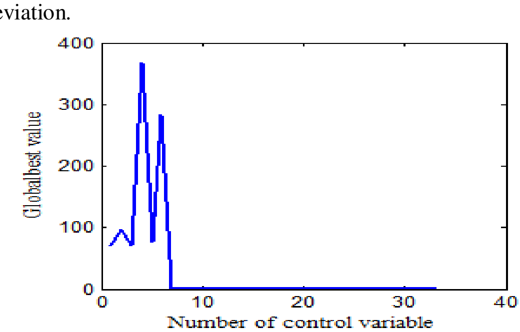

Fig.4 Convergence characteristic of VD

4.1.4 Case 4 –Real power loss minimization

The large amount of reactive power flow results in real power loss in the system. Optimized reactive power flow through the lines can be achieved by minimizing the real power loss.The real power loss(Ploss) can be calculated as

$$P_{loss} = \sum_{K=1}^{N_L} G_k \left[V_i^2 + V_j^2 - 2|V_i||V_j| cos\partial_i - \partial_j\right] \quad (27)$$

Where N_L = total number of lines in system, G_k = Conductance of the line k, V_i, Vj= Magnitude of the sending end and receiving end voltages of the line, ∂_i, ∂_j = Angles of the end voltages

Table 6 shows the control variable setting of voltage deviation, real power loss and reactive power loss minimization. From that Table the cost gained from real power loss without line outage is 45388.21 $/hr and with line outage is 45465.42 $/hr. The convergence characteristic of real power loss is shown in Fig.5.

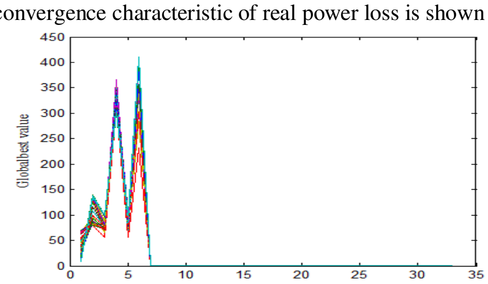

Fig.5 Convergence characteristic of Ploss

4.1.6 Case 6 –Reactive power loss minimization

System security is attained as long as the system operator provides adequate reactive power. Voltage drop in some buses and voltage instability occur as a result of lack of reactive power. An effective management of reactive power should take care of three important requirements: it should maintain the rated voltages at all the buses, maintain the system stability and to utilize the transmission lines to its maximum in order to prevent voltage collapse and minimize power losses and thereby increasing the efficiency. The reactive power cost is given by

$$Cost_{reactive\ power} = a_1 Q^2 + b_1 Q + c_1 \quad (28)$$

Where $a_1 = a\, sin^2\theta$, $b_1 = b \sin\theta$, $c_1 = c$ and a, b, c are the cost coefficients. The convergence characteristic of reactive power loss is shown in Fig.6 .The cost attained from reactive power loss without line outage is 50790.92 $/hr and with line outage is 47989.18 $/hr.

Table. 6 Best control variables settings for voltage deviation, real power loss and reactive power loss minimization

Control Variables	Voltage deviation		Real power loss		Reactive power loss	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
P_{G2}(p.u)	99.9957	100	0.004	0.0004	65.7114	79.2533
P_{G3}(p.u)	93.0965	118.856	140	140	103.2094	96.0196
P_{G6}(p.u)	64.674	0	100	100	70.0016	68.6779
P_{G8}(p.u)	261.6824	416.5684	304.4612	303.314	371.4973	373.9643
P_{G9}(p.u)	100	78.3724	100	99.9998	75.1355	66.1681
P_{G12}(p.u)	289.0638	337.414	410	410	176.0593	229.3761
V_{G1}(p.u)	1.0312	1.0646	1.0501	1.0551	1.0546	1.0391
V_{G2}(p.u)	1.0326	1.0606	1.0436	1.0483	1.0444	1.0199
V_{G3}(p.u)	1.0347	1.0462	1.0458	1.0496	1.0467	1.0391
V_{G6}(p.u)	1.0339	1.0259	1.0373	1.0438	1.0517	1.0489
V_{G8}(p.u)	1.0499	1.0714	1.041	1.0444	1.0565	1.0651
V_{G9}(p.u)	1.0209	1.0237	1.0242	1.0291	1.0381	1.04
V_{G12}(p.u)	1.015	0.984	1.0339	1.0386	1.0528	1.0504
T_{19}(p.u)	1.04	1.04	0.97	0.98	1.05	0.93
T_{20}(p.u)	1.03	0.9	1	1.08	1.02	1.02
T_{31}(p.u)	0.97	1.02	1.04	1.04	1.01	1.07
T_{35}(p.u)	1.01	1	0.96	1.04	0.97	0.99
T_{36}(p.u)	1.05	1.08	1.08	0.94	1.02	1.05
T_{37}(p.u)	1	1.01	1.01	1	1.04	1.02
T_{41}(p.u)	1.03	1.03	0.97	0.98	0.99	1.01
T_{46}(p.u)	0.92	0.92	0.95	0.95	1	0.96
T_{54}(p.u)	0.9	0.9	0.95	0.9	0.97	0.92
T_{58}(p.u)	0.95	0.95	0.97	0.97	0.98	0.96
T_{59}(p.u)	0.98	0.99	0.96	0.96	0.94	1.02
T_{65}(p.u)	1	0.99	0.96	0.96	1	1.01
T_{66}(p.u)	0.9	0.9	0.92	0.93	1.05	1.03
T_{71}(p.u)	0.94	0.99	0.95	0.96	0.97	1
T_{73}(p.u)	1.07	0.98	1.01	0.99	1.02	1.06
T_{76}(p.u)	0.91	0.9	0.98	0.96	1	0.97
T_{80}(p.u)	1.02	1.02	0.97	0.98	1.08	1.09
Q_{C18}(p.u)	0.1	0	0.07	0.21	0.16	0.12
Q_{C25}(p.u)	0.15	0.17	0.15	0.12	0.14	0.16
Q_{C53}(p.u)	0.28	0.25	0.13	0.22	0.26	0.18
P_{G1}(p.u)	366.0361	221.5339	206.5012	208.7589	419.5787	366.5539
Cost($/hr)	48009.788	44572.157	45388.21024	45465.41524	50790.91976	47989.18387

Among those results, reactive power cost without line outage is higher and cost obtained in voltage deviation with line outage is lesser.

Statistical results of 20 runs of IPSO-TVAC for all cases are presented in Table 7. For a large number of individuals continuous or discrete variables are obtainable on a single characteristic in the statistical analysis, occasionally the complete data can be used with a solitary number with lack of losing some information of curiosity. The statistical data provide an idea about absorption of the standards. In this statistical evaluation Minimum value, Maximum value, average value and standard deviation are measured. From this table standard deviation values are less this illustrates the effectiveness of the system. Histogram of cost function for all cases is shown in Fig.7.Simulation time of IPSO-TVAC with all objective functions is shown in Fig.8.

Table 7 Statistical analysis of 20 independent runs of IEEE 57 bus system

Case	Minimum	Maximum	Average	Standard Deviation	Simulation time(sec)		Vdev(v)		Ploss(Mw))		Qloss(Mvar)	
					Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
Fuel cost Minimization($/hr)	41669.14	41681.7	41716.65	4017.173	4010.45	4109.47	1.53	1.44	14.92	16.44	-60.5087	-38.56
Voltage Deviation (p.u.)	0.616539	0.76906	0.695412	0.05554	4074.39	5184.86	1.6	0.79	21.29	28.39	-31.1508	16.25
Real power loss minimization(MW)	10.0041	10.7539	10.1961	0.26264	5466.25	4358.16	1.21	1.53	10.28	20.36	-73.5359	-31.48
Reactive power loss minimization(MVAR)	6.17E-12	1.69E-05	2.45E-06	6.39E-06	7496.81	14275.30	1.23	1.6	29.35	21.43	2.63E-04	-17.17

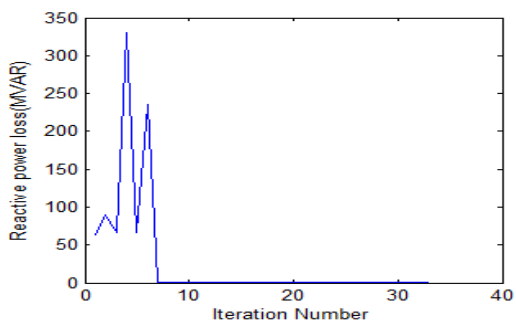

Fig. 6 Convergence characteristic for Reactive power loss

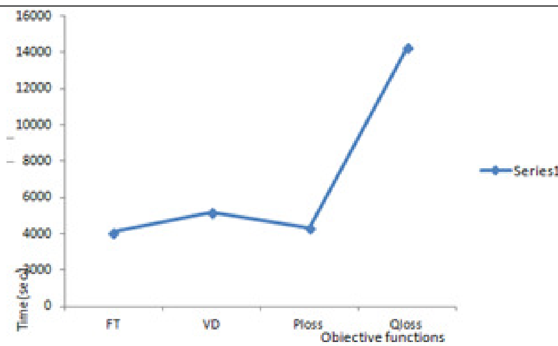

Fig. 8. Simulation time of PSO with all objective functions

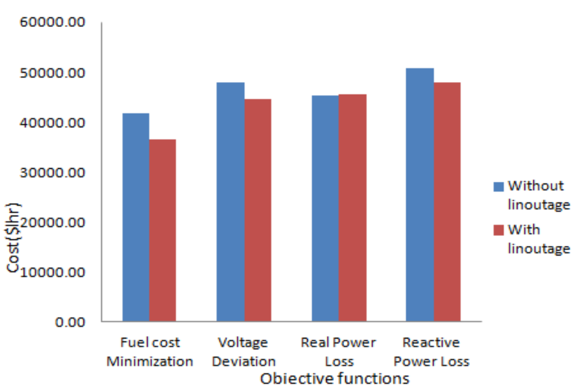

Fig.7. Histogram of cost function for all cases

5.0 Conclusion

This paper has proposed an Improved PSO with Time Varying Acceleration Coefficients (IPSO-TVAC) algorithm for solving Optimal Power Flow problem. Penalty parameter free approach has been used to handle the inequality constraints on dependent variables. In this proposed approach IEEE 57-bus test system have been tested to minimize the fuel cost, reactive power loss, real power loss and voltage deviation under normal and contingency conditions. The proposed algorithm simulation results are compared with literature reports. The results show that the system becomes optimum as well as secure because of the proposed algorithm. Hence, it is clear that for large power systems the proposed algorithm gives quality solutions when compared to the other algorithms

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