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Optimal Power Flow Using Improved Pso With Time Varying Acceleration Coefficients

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ABSTRACT: Optimal Power Flow (OPF) is an important tool for power system operators both in planning and operation of electric power systems. In this paper, an improved PSO with time varying acceleration coefficients (IPSO-TVAC) algorithm is employed for solving the OPF problem. Generator real power outputs (except at the slack bus), generator voltages, transformer tap settings and reactive power injections are taken as the control variables. Penalty parameter-less constraint handling scheme is used to handle the inequality constraints. Minimization of total fuel cost is considered as the objective function. The proposed method is tested on the standard IEEE 30-bus and IEEE 57-bus test systems and the results are compared with the results obtained by other techniques reported in the literature. The simulation results show the effectiveness of the proposed method for obtaining secured optimal operation of power system.

KEYWORDS: Cost minimization, Improved PSO, Optimal Power Flow, penalty parameter-less approach, time varying acceleration coefficients.

I. INTRODUCTION

Optimal power flow (OPF) is an important tool for power system operators both in planning and operation of electric power systems. OPF was first introduced by Carpentier in 1962 [6]. OPF is a nonlinear multimodal optimization problem with non-smooth search space. The function of OPF is to optimize one or more objective functions by the optimal adjustment of power system control variables while satisfying a set of equality and inequality constraints.

Several conventional methods have been proposed to solve the OPF problem [2]–[5]. But those methods suffer from disadvantages like premature convergence and fail to deal with systems having non-convex, non-differentiable objective functions and constraints. In order to overcome the drawbacks of the conventional methods, several heuristic optimization algorithms have been proposed to solve the OPF problem [8], [9], [12]-[14], [17].

In [8], M.A.Abido et al. proposed DE to solve optimal power flow problem on the standard IEEE 30-bus test system. In [9], A.Battacharya et al. employed biogeography based optimization (BBO) to solve the OPF problem on IEEE 30-bus system with different objectives. BBO searches for the global optimum through migration and mutation. In [12], M.A.Abido employed PSO algorithm to solve the OPF problem on IEEE 30-bus test system. In [13], Mahmood Joorabian et al. solved the OPF problem using the new hybrid fuzzy particle swarm optimisation and Nelder–Mead algorithm (HFPSO–NM). In [14], M.Rezaei Adaryani et al. proposed ABC algorithm for solving OPF problem on IEEE 9-bus system, IEEE 30-bus system and IEEE 57-bus system with different objective functions. In [17], Serhat Duman et al. proposed gravitational search algorithm (GSA) to solve the OPF problem. The proposed approach was tested on the standard IEEE 30-bus and 57-bus test systems with different objective functions.

The OPF control variables include both continuous and discrete variables. However, in [8], [9], [12], [13],[17], the transformer tap settings and reactive power injections by shunt devices are taken as continuous variables instead of practical discrete values.

PSO algorithm is a population based stochastic optimization technique, motivated by the behaviour of organisms such as fish schooling and bird flocking. It was introduced by Kennedy and Eberhart [18]. In recent years, PSO algorithm has been successfully employed to solve many optimization problems in power systems such as reactive power optimization, transmission expansion planning, relieving transmission congestion, optimal placement of multiple distributed generator units and so on. In this paper IPSO-TVAC algorithm is proposed to solve the mixed-integer OPF problem subject to a set of equality and inequality constraints. Penalty parameter-less constraint handling scheme is used

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to handle the inequality constraints, while mixed integer handling method is used to handle OPF control variables. Minimization of total fuel cost is considered as the objective function. The proposed method is tested on the standard IEEE 30-bus and IEEE 57-bus systems. Simulation results show that the proposed approach provides quality solutions for OPF problem.

II. PROBLEM FORMULATION

The OPF problem is formulated as a mixed integer nonlinear optimization problem. The control variables include generator real power outputs P_G except at the slack bus, generator voltages V_G and transformer tap settings T and reactive power injections Q_C. 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 comprise of power flow equations. The inequality constraints include the constraints on control and dependent variables. The generator real power outputs except at the slack bus and generator voltages are continuous variables, while the transformer tap settings and the reactive power injections of the shunt compensators are discrete variables.

Objective function: Minimization of total fuel cost

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

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

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

Constraints

The equality constraints represent the real and reactive power flow equations. The inequality constraints represent the system operational and security limits given as follows.

$$V_{G_i}^{min} \le V_{G_i} \le V_{G_i}^{max}, \quad i = 1, \dots, N_G \tag{2}$$
$$P_{G_i}^{min} \le P_{G_i} \le P_{G_i}^{max}, \quad i = 1, \dots, N_G \tag{3}$$
$$Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max}, \quad i = 1, \dots, N_G \tag{4}$$
$$T_i^{min} \le T_i \le T_i^{max}, \quad i = 1, \dots, N_T \tag{5}$$
$$Q_{C_i}^{min} \le Q_{C_i} \le Q_{C_i}^{max}, \quad i = 1, \dots, N_C \tag{6}$$
$$V_{L_i}^{min} \le V_{L_i} \le V_{L_i}^{max}, \quad i = 1, \dots, N_{PQ} \tag{7}$$
$$S_{L_i} \le S_{L_i}^{max}, \quad i = 1, \dots, N_L \tag{8}$$

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

Incorporation of constraints

The equality constraints can be satisfied by Newton Raphson (NR) load flow solution. 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 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 then they are clamped to their respective upper or lower limit using (9).

$$u_i = \begin{cases} u_i^{max} & \text{if } u_i > u_i^{max} \\ u_i^{min} & \text{if } u_i < u_i^{min} \end{cases} \tag{9}$$

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

Hence, penalty parameter less constraint handling scheme [15] is used to handle only the inequality constraints of the dependent variables. These constraints are incorporated by modifying the objective function as shown in (10).

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

where f_{max} is the objective function value of the worst feasible solution in the population, CV is the overall constraint violation and is given by (11).

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

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}.

III. IMPROVED PSO WITH TIME VARYING ACCELERATION COEFFICIENTS

Conventional PSO

PSO is a population based algorithm inspired by the movements of a flock of birds. In the PSO algorithm, each particle can be represented by its position and velocity. The particles change their positions by flying around in a multidimensional search space until a relatively unchanged position has been encountered. In the search space, particle best is the best position corresponding to the best fitness encountered so far by a particle and is denoted as Pbest, whereas global best is the best position encountered so far among the whole population and is denoted as Gbest. The velocity and position of each particle is updated using (12) and (13).

$$V_{j,d}^{(k+1)} = wV_{j,d}^{k} + c_1 rand_1 (Pbest_{j,d}^{k} - X_{j,d}^{k}) + c_2 rand_2 (Gbest_{j,d}^{k} - X_{j,d}^{k}) \quad (12)$$

$$X_{j,d}^{(k+1)} = X_{j,d}^{k} + C\, V_{j,d}^{(k+1)} \quad (13)$$

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 and c2 are the cognitive and social component acceleration coefficients; rand1 and rand2 are the uniformly distributed random numbers between 0 and 1; $X_{j,d}^{k}$is the position of particle j in the d[th] dimension at iteration k; C is the constriction factor calculated using (14); w is the inertia weight, which is linearly decreasing as the generations proceed and is updated using (15).

$$C = \frac{2}{\left(2-\phi-\sqrt{\phi^2-4\phi}\right)} \quad (14)$$

$$w = W_{max} - \frac{(W_{max}-W_{min})}{G_{max}} * G \quad (15)$$

where Φ=4.1; W_{max} and W_{min} are the initial and final values of inertia weight respectively; G_{max} is the maximum number of generations; G is the current generation.

To control excessive roaming of particles, the velocity of each particle obtained using (12) is restricted by their upper and lower limits, and is given by (16).

$$V_d^{min} \le V_d \le V_d^{max} \quad (16)$$

where V_d^{max} is the velocity maximum and V_d^{min} is the velocity minimum in the d[th] dimension and is given by (17) and (18).

$$V_d^{max} = \frac{\left(x_d^{max} - x_d^{min}\right)}{K} \quad (17)$$

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

where K=5 is the parameter to control the number of intervals in the d[th] dimension [10].

Even though PSO algorithm can determine a better solution in a fast convergence rate, its ability to fine tune the optimal solution is lacking because of diversity at the end of the search.

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IPSO-TVAC

In order to prevent premature convergence, the proposed IPSO-TVAC algorithm employed crossover operator and time varying acceleration coefficients to enhance particle diversity and improve global searching capability. The position of particle j, obtained in (13) is mixed with $Pbest_j$ to generate the new position as shown in (19).

$$x_{j,d}^{k+1} = \begin{cases} x_{j,d}^{k+1} & \text{if rand } \le C_r \\ Pbest_{j,d}^{k} & \text{otherwise} \end{cases} \quad (19)$$

where C_r is the crossover probability. In the conventional PSO algorithm, c_1 and c_2 are fixed as 2.0. Relatively high value of the social component c_2 in comparison with cognitive component c_1 leads particles being trapped into local optimum and relatively high value of cognitive component results to wander the particles around the search space. In order to obtain solution quality, the acceleration coefficients are updated using the following equations:

$$c_1 = (c_{1f} - c_{1i}) + \left(\frac{G}{G_{max}}\right) * c_{1i} \quad (20)$$

$$c_2 = (c_{2f} - c_{2i}) + \left(\frac{G}{G_{max}}\right) * c_{2i} \quad (21)$$

where c_{1i} and c_{2i} are the initial values of c_1 and c_2; c1f 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.

Mixed integer handling method

The control variables involve both the continuous and discrete 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 (22) while the discrete variables are generated randomly using (23). Thus, the initial population contains the control variables such as generator real power outputs (except slack bus) and generator voltages in continuous form and transformer tap settings 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 (12) and (13). While evaluating the fitness function, the values obtained for the discrete variables using the proposed algorithm are rounded to their nearest discrete values using (24).

$$x_{cv} = \text{rand} * (\text{high} - \text{low}) + \text{low} \quad (22)$$

$$x_{dv} = \min + n_k * \Delta s \quad (23)$$

$$x_{dv,d} = \text{round}\left(\frac{x_{dv,d}}{\Delta s}\right) * \Delta s \quad (24)$$

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}; n_k is the number of positions; Δs is the step size; $x_{dv,d}$ represents the discrete control variable at d^{th} dimension.

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Implementation of IPSO-TVAC for OPF problem

The flowchart for solving OPF problem is depicted in Fig.1.

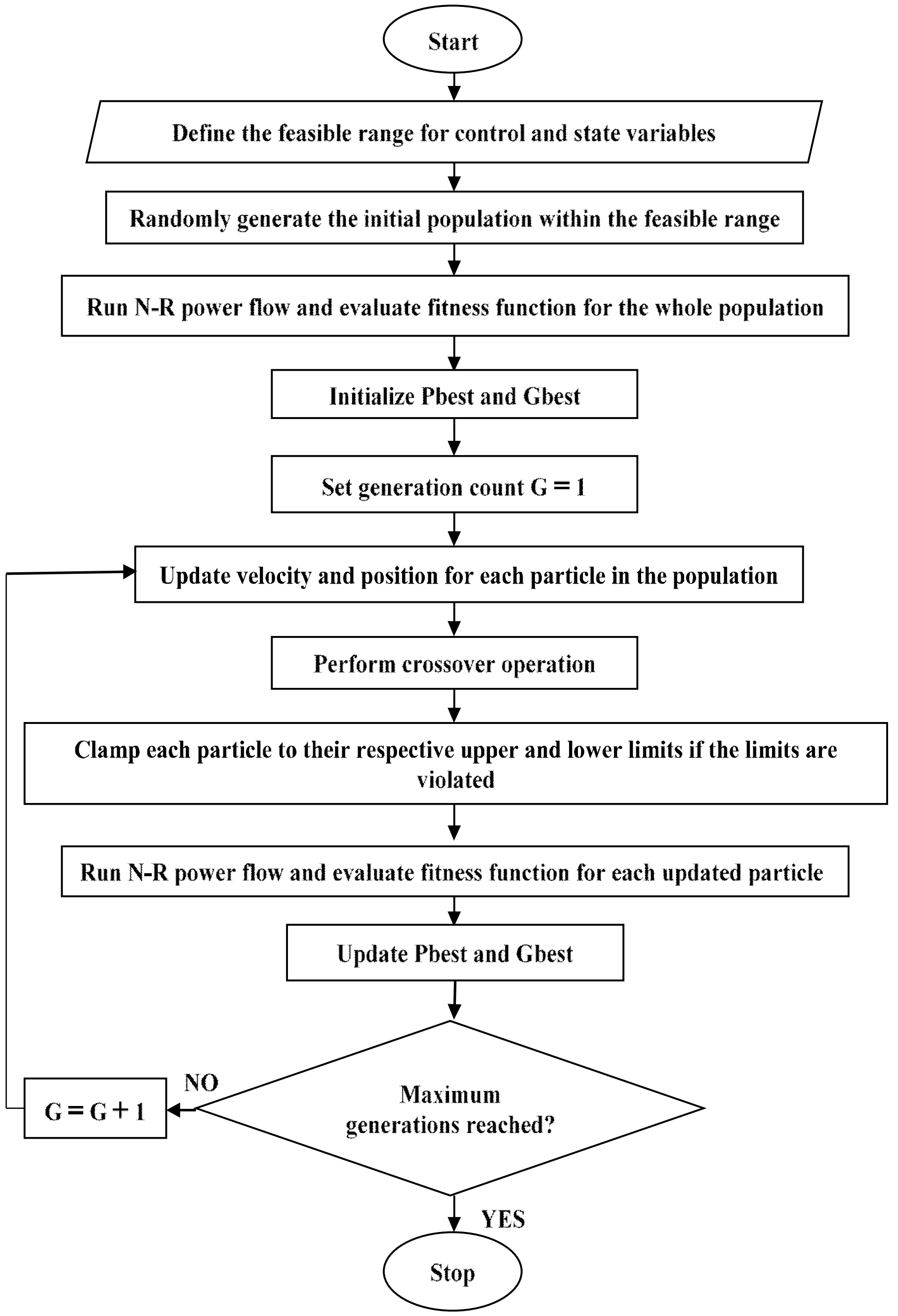

Figure 1. Flowchart of the proposed IPSO-TVAC algorithm for solving OPF

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 (22) and (23).
3. Run N-R power flow and evaluate fitness function for each particle in the population using (10).

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4. Repeat step 3 until the fitness function for all the particles in the population is evaluated.
5. The fitness values calculated using (10) for the initial particles of the population are set as the initial Pbest values. The best value among all the Pbest value is identified as Gbest.
6. Set the maximum number of generations and set generation count=1.
7. Update the velocity using (12) and apply velocity limits using (16).
8. Update the position using (13) and perform crossover using (19).
9. If the inequality constraints of the control variables are violated, then clamp them into the feasible range using (9); else go to step 10.
10. Run N-R power flow and evaluate fitness function for each updated particle using (10).
11. Update Pbest and Gbest. Pbest is updated based on the following conditions.
    - 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. Increment the generation count.
13. Repeat step 7 to step 12 until the maximum generation is reached.

IV. SIMULATION RESULTS

The proposed IPSO-TVAC algorithm has been applied to solve the OPF problem in IEEE 30-bus and IEEE 57-bus test systems. Power flow calculation by Newton-Rapshon method is performed using MATPOWER software package version 4.0b4 [7]. In MATPOWER, Interior point method is used to solve the OPF problem. The parameter settings for the IPSO-TVAC algorithm are shown in Table I.

IEEE 30-bus system

The IEEE 30-bus system has 41 lines, 6 generators, 9 capacitor banks, and 4 tap setting transformers. The system data can be found in [15].The total active and reactive power demands of the system are 283.4 MW and 126.2 MVAr, respectively.

TABLE I. PARAMETER SETTINGS FOR IPSO-TVAC

Parameter	Setting	
Wmax [11]	0.9	
W_{min} [11]	0.4	
c_{1i}, c_{2f} [1]	2.5	
c_{1f}, c_{2i} [1]	0.5	
C_r	0.6	
No. of iterations	200	
Trial runs	30	
Population size N_P	IEEE 30-bus system	50
	IEEE 57-bus system	165

The system data can be found in [5]. The voltage magnitude limits of the generator buses and load buses are between 0.95 - 1.1 p.u. and 0.95 - 1.05 p.u., respectively. The transformer tap settings have 20 discrete steps of 0.01 p.u., and can be varied in the range 0.9 - 1.1 p.u. The reactive power injections of the shunt compensators have 10 discrete steps of 0.01 p.u., and can be varied in the range 0 - 0.05 p.u. The cases considered are as follows.

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Case 1- Fuel cost minimization:

In this case, the generator cost curves are modeled by quadratic functions as defined in (1). The minimum fuel cost obtained by the proposed IPSO-TVAC approach is 800.814 \$/hr with an average of 800.9205 \$/hr and a maximum of 801.0812 \$/hr. The convergence characteristics corresponding to the minimum fuel cost is shown in Fig. 2.

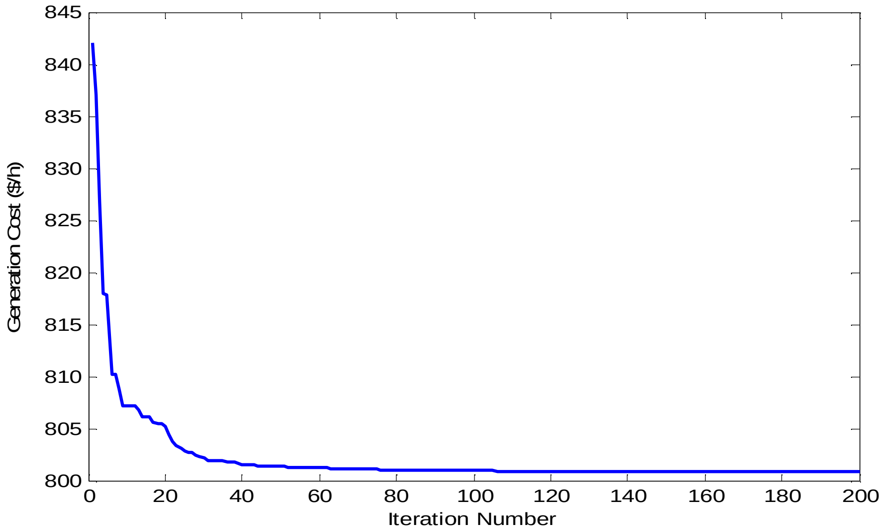

Figure 2. Convergence characteristics for case 1 of IEEE 30-bus system

TABLE II. COMPARISON OF RESULTS OBTAINED FOR DIFFERENT CASES IN VARIOUS TEST SYSTEMS

Method	IEEE 30-bus system		IEEE 57-bus system
	F_T (\$/hr)		F_T (\$/hr)
	Case 1	**Case 2**	
IPSO-TVAC	800.814	840.323	41669.14
GSA [17]	798.675[a]	-	41695.8717[a]
BBO [9]	799.111[a]	-	-
DE [8]	799.289[a]	-	-
PSO [12]	800.41[a]	-	-
HFPSO-NM [13]	794.954[a]	-	-
ABC [14]	800.66	-	41693.9
MATPOWER	801.68	842.63	41737.79

[a] Infeasible solution.

The result obtained using the proposed method is compared with those reported in the literature and is presented in Table II. The optimum settings of control variables corresponding to this case is presented in Table III. From Table II, it is clear that better result is obtained using ABC algorithm. However, the result obtained using the proposed IPSO-TVAC algorithm is also a feasible solution. Hence, the proposed IPSO-TVAC algorithm is one of the best algorithms for solving the OPF problem. However, the results marked with '[a]' in Table II, are infeasible solutions. Reasons for

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infeasibility of those results except for [13] are reported in [14]. For the optimum setting of control variables reported in [13], there are voltage magnitude violations at all load buses except 26 and 30. Also, the reactive power of generator at bus 1 has violated its minimum limit. In Table II MATPOWER represents the result obtained for OPF using Interior point method which is a conventional method. From Table II it is clear that the cost obtained using the proposed algorithm is less than the cost obtained by MATPOWER.

TABLE III. COMPARISON OF OPF CONTROL VARIABLES FOR DIFFERENT CASES IN IEEE 30-BUS SYSTEM

Control Variable	Case 1	Case 2
P_{G2}	0.48739	0.651647
P_{G5}	0.21384	0.255174
P_{G8}	0.21234	0.35
P_{G11}	0.11977	0.21065
P_{G13}	0.12	0.187975
V_{G1}	1.08467	1.09968
V_{G2}	1.06519	1.038508
V_{G5}	1.03356	1.015541
V_{G8}	1.03763	1.035371
V_{G11}	1.08703	1.059292
V_{G13}	1.04407	1.08702
T_{11}	1.1	1.01
T_{12}	0.9	0.96
T_{15}	0.97	1.04
T_{36}	0.97	0.99
Q_{C10}	0.03	0.05
Q_{C12}	0.03	0.01
Q_{C15}	0.05	0.04
Q_{C17}	0.05	0.05
Q_{C20}	0.05	0.04
Q_{C21}	0.05	0.04
Q_{C23}	0.03	0.03
Q_{C24}	0.05	0.05
Q_{C29}	0.02	0.03
Fuel cost ($/hr)	**800.814**	**840.323**
P_{G1}	1.77182	1.296311

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 [16]. For this case, the minimum fuel cost obtained using the proposed IPSO-TVAC approach is 840.323 $/hr with an average of 841.6305 $/hr and a maximum of 842.0694 $/hr. The optimum settings of control variables corresponding to this case is presented in Table III. From Table II, it is clear that the cost obtained by the proposed method is less than the cost obtained by MATPOWER. Fig. 3 shows the system voltage profile after 1-2 line outage. From fig. 3 it is clear that all the bus voltages are within the feasible range even under the contingency condition. This shows the effectiveness of the proposed approach.

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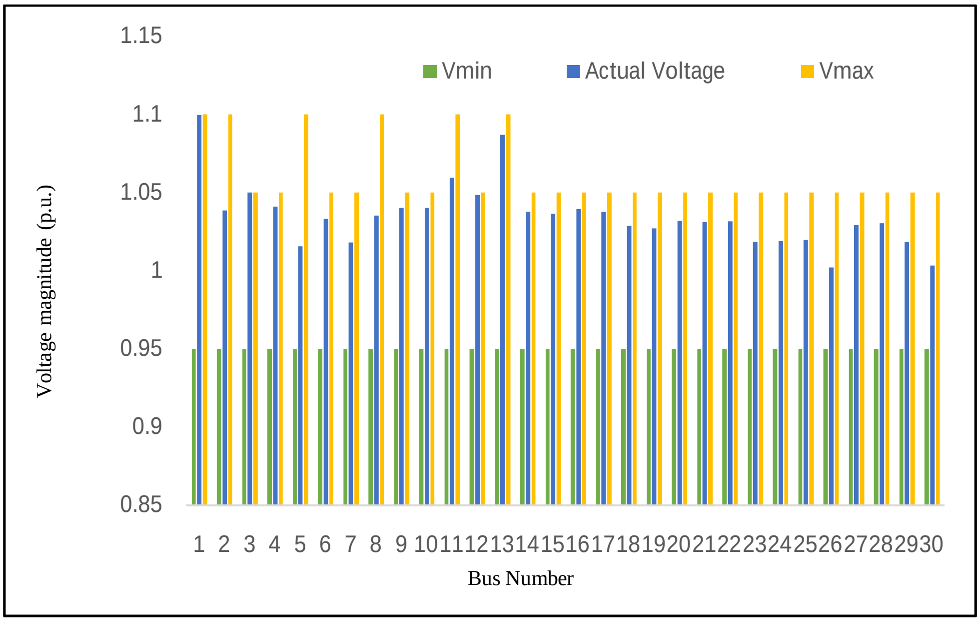

Figure 3. System voltage profile for case 2 of IEEE 30-bus system

IEEE 57-bus system

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 [17]. 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 0.01 p.u., and can be varied in the range 0.9 -1.1 p.u. The reactive power injections of the shunt compensators have 30 discrete steps of 0.01 p.u., and can be varied in the range 0 – 0.30 p.u.

Minimization of total fuel cost is the objective function considered here. In this case, the minimum fuel cost obtained by the proposed IPSO-TVAC algorithm in 30 independent trail runs is 41669.14 $/hr with an average of 41681.74 $/hr and a maximum of 41716.65 $/hr. The optimum settings of control variables corresponding to this case is presented in Table IV. The convergence characteristics corresponding to the minimum fuel cost is shown in Fig. 4. From Table II, it is clear that the minimum cost obtained using the proposed method is less than the cost obtained by the heuristic algorithms [14], [17] reported in literature and also the cost obtained by MATPOWER. Also, the best solution mentioned in [17] is an infeasible solution because 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. This shows the effectiveness and solution quality of the proposed approach when compared to the other algorithms. From Table II, it is also clear that the proposed algorithm gives better results for large systems.Table V presents the results obtained in various test systems for 30 independent runs

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TABLE IV. OPTIMAL SETTING OF CONTROL VARIABLES FOR FUEL COST MINIMIZATION IN IEEE 57-BUS SYSTEM

Control Variable (p.u.)		**Control Variable (p.u.)**	
P_{G2}	0.897332	T_{36}	1.02
P_{G3}	0.447366	T_{37}	1.04
P_{G6}	0.70858	T_{41}	1
P_{G8}	4.60662	T_{46}	0.95
P_{G9}	0.964515	T_{54}	0.9
P_{G12}	3.613781	T_{58}	0.98
V_{G1}	1.063966	T_{59}	0.97
V_{G2}	1.061763	T_{65}	0.98
V_{G3}	1.054539	T_{66}	0.94
V_{G6}	1.062121	T_{71}	0.99
V_{G8}	1.074313	T_{73}	0.99
V_{G9}	1.050827	T_{76}	0.97
V_{G12}	1.055826	T_{80}	1.01
T_{19}	1	Q_{C18}	0.13
T_{20}	1.03	Q_{C25}	0.13
T_{31}	1.03	Q_{C53}	0.12
T_{35}	1.01	$\mathbf{P_{G1}}$	1.418812
Fuel Cost ($/hr)	41669.14		

TABLE V. RESULTS OBTAINED IN VARIOUS TEST SYSTEMS FOR 30 INDEPENDENT TRIAL RUNS

Fuel cost ($/hr)		Minimu	Average	Maximum
IEEE 30-bus system	Base case	800.814	800.9205	801.0812
	1-2 line outage	840.323	841.6305	842.0694
IEEE 57-bus system	Base case	41669.14	41681.74	41716.65

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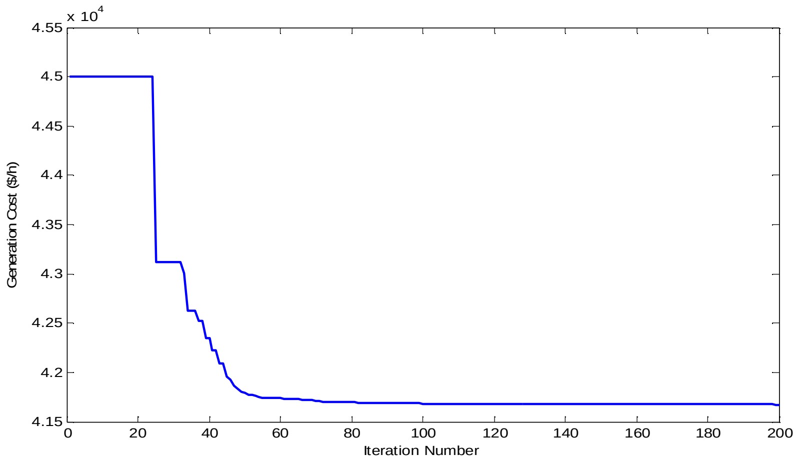

Figure 4. Convergence characteristics for fuel cost minimization in IEEE 57-bus system

V. CONCLUSION

This paper has proposed an improved PSO with time varying acceleration coefficients (IPSO-TVAC) algorithm for solving the OPF problem. Penalty parameter-less constraint handling scheme was used to handle the inequality constraints on dependent variables. The proposed approach was tested on standard IEEE 30-bus and IEEE 57-bus test systems for minimization of fuel cost. The simulation results were compared with those reported in the literature. The results show the effectiveness and solution quality of the proposed algorithm when compared to the other algorithms. In future, the proposed algorithm can be used to incorporate an optimal pricing scheme in deregulated electricity.

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