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Optimal power flow by particle swarm optimization with an aging leader and challengers

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Abstract

Optimal power flow (OPF) is defined as the optimization of operating states of a power system and the corresponding settings of control variables. In this paper, a particle swarm optimization (PSO) with an aging leader and challengers (ALC-PSO) is applied for the solution of OPF problem of power system. This study is implemented on modified IEEE 30-bus test power system with different objectives that reflect minimization of either fuel cost or active power loss or sum of total voltage deviation. The results presented in this paper demonstrate the potential of the proposed approach and show its effectiveness and robustness for solving the OPF problems over the other evolutionary optimization techniques surfaced in the recent state-of-the-art literature.

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1. Introduction

The main purpose of OPF is to schedule the power generation in such a way that minimizes the fuel cost while satisfying all the equality and inequality constraints. In addition to the minimization of fuel cost, the OPF may also be used to achieve the other benefits such as reduction of system loss, improvement of voltage profile or system security. Thus, the objective of OPF is to find steady state operating point which minimizes generation cost, system loss, voltage deviation etc while maintaining an acceptable system performance in terms of limits on generators' real and reactive powers, line flows, outputs of various compensating devices etc.

In recent years, many heuristic algorithms such as genetic algorithm (GA) (Deveraj & Yegnanarayana 2005), improved GA (IGA) (Lai & Ma 1997), enhanced GA (EGA) (Bakirtzis *et al.* 2002), evolutionary programming (EP) (Somasundaram *et al.* 2004), differential evolution (DE) (Ela *et al.* 2010), particle swarm optimisation (PSO) (Abido 2002), biogeography-based optimization (BBO) (Bhattacharya & Chattopadhyay 2011), gravitational search algorithm (GSA) (Duman *et al.* 2012) etc have been proposed for solving the OPF problem without any restrictions on the shape of the cost curves. The results reported were promising and encouraging for further research in this direction.

Specially, PSO has received increased attention from researchers because of its novelty and searching capability. PSO algorithm is one of the swarm intelligence techniques based on simulating the food-searching behaviour of birds (Kennedy & Eberhart 1995). However, constant emphasis is being given by the researchers' pool towards its improvement in performance, since the original PSO proposed in (Kennedy & Eberhart 1995) is prone to suffer from the so-called "explosion" phenomena.

Recently, many improved versions of PSO viz. PSO with adaptive inertia weight (PSO-w), PSO with a constriction factor (PSO-CF), mixed integer PSO (MIPSO), hybrid PSO (HPSO), discrete PSO (DPSO) etc were proposed in (Shi & Eberhart 1998; . Clerc & Kennedy 2002; Gaing 2005; AlRashidi & El-Hawary 2007; Gomez-Gonzaleza *et al.* 2012).

It is the general law of nature that every organism in the earth ages and has a limited lifespan. With the passage of time, leader of the colony becomes old and feeble. And this old leader has no longer the capability to lead the colony unless or otherwise it is challenged by a new and young challenger with great deal of enthusiasm and motivation to accomplish certain targets. Thus, aging provides opportunities for the other individuals of the colony to challenge the leadership capability of the leader. Based on these concepts, a modified PSO called as PSO with aging leader and challenges (ALC-PSO) is represented in the literature (Chen *et al.* 2013).

In ALC-PSO (Chen *et al.* 2013), the lifespan of the leader is adaptively tuned in accordance with the leader's leading power. If a leader shows strong leading power, it lives longer to attract the swarm toward better positions. Otherwise, if a leader fails to improve the swarm and gets old, new particles emerge to challenge and claim the leadership, which brings in diversity. In this way, the concept "aging" in ALC-PSO actually serves as a challenging mechanism for promoting a suitable leader to lead the swarm. In this way, natural aging mechanism of the organism has been modelled into ALC-PSO.

In the present work, the ALC-PSO is applied for the solution of OPF problem of power systems. Modified IEEE 30-bus power system is adopted as standard power network whose OPF problem is solved with the objectives as (a) cost minimization, (b) transmission active power loss (P_{Loss}) minimization and (c) reduction of sum of total voltage deviation (TVD). The results are compared to other computational intelligence-based techniques surfaced in the recent literature.

The rest of this paper is organized as follows. In Section II, mathematical problem of the OPF work is presented. Section III describes the basic PSO. In Section IV, ALC-PSO is narrated. Simulation results are discussed in Section V. Finally, conclusions of the present paper are drawn in Section VI.

2. Problem formulation of OPF

The objective of OPF is to minimize the objective function while satisfying all the equality and inequality constraints of power system. The different individual objective functions may be formulated as in (Alsac & Stott 1974; AlRashidi & El-Hawary 2007).

2.1 Minimization of fuel cost: The aim of this type of problem is to minimize the total fuel cost and it may be formulated as in (1).

$$\text{Minimize } \mathrm{FC}(P_G) = \left(\sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \right) \tag{1}$$

2.2 Minimization of transmission loss: Mathematical formulation of this type objective function is given as in (2).

$$\text{Minimize } P_{Loss} = \sum_{k=1}^{NTL} G_k (V_i^{\,2} + V_j^{\,2} - 2|V_i||V_j| \cos\delta_{ij}) \tag{2}$$

2.3 Minimization of TVD: This problem aims to minimize the voltage deviation of all the bus from 1.0 p.u. and may be formulated as in (3).

$$\text{Minimize } TVD = \sum_{i=1}^{N} |V_i - V_{ref}| \tag{3}$$

The equality and inequality constraints of OPF problem may be formulated as in (4) and (5), respectively,

$$\left. \begin{aligned} P_{Gi} - P_{Li} &= \sum_{j=1}^{NG} |V_i||V_j| (G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij}) \\ Q_{Gi} - Q_{Li} &= \sum_{j=1}^{NG} |V_i||V_j| (G_{ij} \sin\delta_{ij} - B_{ij} \cos\delta_{ij}) \end{aligned} \right\} \tag{4}$$

$$\left.\begin{array}{ll} V_{Gi}^{\min} \le V_i \le V_{Gi}^{\max} & i = 1, 2, \ldots, NG \\ P_{Gi}^{\min} \le P_i \le P_{Gi}^{\max} & i = 1, 2, \ldots, NG \\ Q_{Gi}^{\min} \le Q_i \le Q_{Gi}^{\max} & i = 1, 2, \ldots, NG \\ V_{Li}^{\min} \le V_i \le V_{Li}^{\max} & i = 1, 2, \ldots, NL \\ S_{l_i} \le S_{l_i}^{\max} & i = 1, 2, \ldots, NTL \\ Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} & i = 1, 2, \ldots, NC \end{array}\right\} \tag{5}$$

where,

$FC(P_G)$: total fuel cost in \$/h.

P_{Loss} : the total power losses,

NG , NL : number of generator and load buses respectively,

NTL : number of transmission lines

NT : number of regulating transformers,

NC : number of shunt compensators,

a_i , b_i , c_i : cost coefficients of i-th generator as in TABLE I,

V_i , Vj : voltage of the i-th and the j-th bus,

P_{Gi} , Q_{Gi} : active and reactive power of the i-th generator, P_{Li} , Q_{Li} : active and reactive power of the i-th load bus,

G_{ij} , Q_{ij} , δ_{ij} : conductance, admittance and phase difference of voltages between the i-th and the j-th bus.

The scripts "min" and "max" denote the corresponding lower and upper limits, respectively.

Table 1. Cost Coefficients for Modified IEEE 30-Bus System

Coefficients	Unit					
	1	***2***	***3***	***4***	***5***	***6***
a_i	0.00375	0.0175	0.0625	0.00834	0.025	0.025
b_i	2	1.75	1	3.25	3	3
c_i	0	0	0	0	0	0

3. Particle swarm optimization and discussions

PSO (Kennedy & Eberhart 1995) is a swarm intelligence based algorithm inspired by the social dynamics and an emergent behaviour which arises in socially organized colonies. PSO algorithm exploits a population of individuals to probe promising regions of search space. In this context, population is called *swarm* and individuals are called *particles* or *agents*. In PSO algorithms, each particle moves with an adaptable velocity within regions of decision space and retains a memory of the best position it has ever encountered. The best position ever attained by each particle of the swarm is communicated to all other particles.

PSO is initialized with a population of particles randomly positioned in a d-dimensional search space. Each particle in the population maintains two vectors viz. a velocity vector and a position vector. During each generation, each particle updates its velocity and position by learning from the particle's own historically best position and the best position found by the entire swarm so far. Let, $\vec{V}_i(t)\{\vec{v}_i^1(t), \vec{v}_i^2(t), \ldots, \vec{v}_i^d(t)\}$ and $\vec{X}_i(t)\{(\vec{x}_i^1(t), \vec{x}_i^2(t), \ldots, \vec{x}_i^d(t)\}$ be the i-th particle's velocity vector and position vector at t-th iteration, respectively, and N_P be the number of particles in a population. In the original PSO, update rules for the velocity and the position vectors are

$$\vec{v}_i^j(t+1) \leftarrow w(t)\times \vec{v}_i^j(t) + c_1 \times r_1^j \times \{\vec{x}_{pBest}^j - \vec{x}_i^j(t)\} + c_2 \times r_2^j \times \{\vec{x}_{gBest}^j - \vec{x}_i^j(t)\} \tag{6}$$

$$x_i^j(t+1) \leftarrow x_i^j(t) + v_i^j(t+1) \tag{7}$$

where $\vec{x}_{pBest_i}$ $(\vec{x}_{pBest_i}^{\,1}, \vec{x}_{pBest_i}^{\,2}, \ldots, \vec{x}_{pBest_i}^{\,d})$ is the historical best position of particle $i\ (i = 1, 2, \ldots, N_p)$, $\vec{x}_{gBest}$ $(\vec{x}_{gBest}^{\,1}, \vec{x}_{gBest}^{\,2}, \ldots, \vec{x}_{gBest}^{\,d})$ is the historical best position of the entire swarm, c_1 and c_2 are two parameters to weight the relative importance of $\vec{x}_{pBest_i}$ and $\vec{x}_{gBest}$, respectively, r_1^j and r_2^j are random numbers uniformly distributed in [0, 1] and $j\,(j = 1, 2, \ldots, d)$ represents the *j*-th dimension of the search space. The symbol "×" represents the component-wise product of the corresponding vectors. In (5), w is the inertia weight, which controls the degree that the velocity of a particle at iteration t influences the velocity of that particle at iteration (t + 1) and its value at t-th iteration is determined by (8).

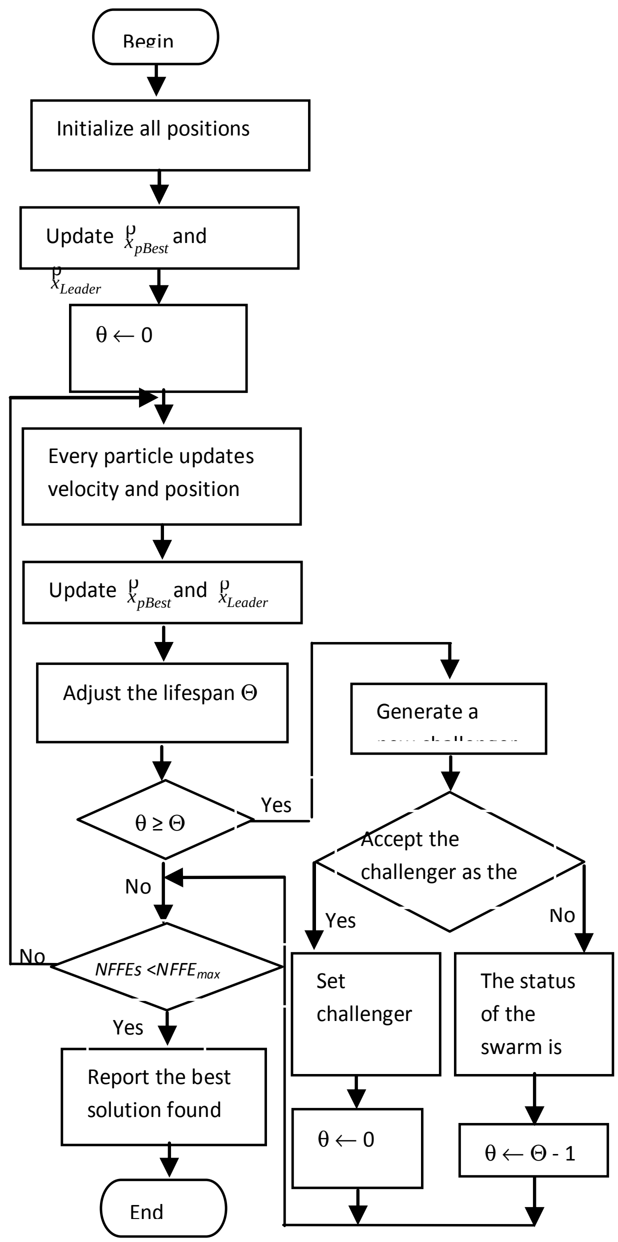

Figure 1. Flow chart of the ALC-PSO

$$w(t) \leftarrow \left[w_{max} - \frac{w_{max} - w_{min}}{T_{max}} \times t \right] \tag{8}$$

where, T_{max} is the maximum number of iterations. In PSO model, according to (6) and (7), particles share information through swarm attractor $\vec{x}_{gBest}$ and evoke memories by particle $\vec{x}_{pBest_i}$.

4. PSO with an aging leader and challengers

In ALC-PSO (Chen et al. 2013), it is assumed that the leader of the swarm ages within a limited lifespan. The lifespan is adaptively adjusted according to the leader's leading power. When the lifespan is exhausted, the leader is challenged and replaced by newly generated particles. Therefore, the leader in ALC-PSO is not necessarily being the $\vec{x}_{gBest}$ but a particle with adequate leading power guaranteed by the aging mechanism.

To differentiate the leader in ALC-PSO from the $\vec{x}_{gBest}$ of original PSO (Kennedy & Eberhart 1995), the leader is denoted by $\vec{x}_{Leader}$ ($\vec{x}_{Leader}^{\,1}$, $\vec{x}_{Leader}^{\,2}$, ... , $\vec{x}_{Leader}^{\,d}$). The velocity update rule of (6) is, thus, changed to

$$\vec{v}_i^{\,j}(t+1) \leftarrow w(t)\times\vec{v}_i^{\,j}(t)+c_1\times r_1^j\times\{\vec{x}_{pBest}^{\,j}-x_i^j(t)\}+c_2\times r_2^j\times\{\vec{x}_{Leader}^{\,j}-\vec{x}_i^{\,j}(t)\} \tag{9}$$

The flowchart of ALC-PSO is illustrated in Figure 1 and the steps involved are given as (Chen *et al.* 2013)

Step 1. *Initialization:* The initial positions of all the particles are randomly generated within their respective minimum and maximum values with velocities initialized to 0. Historical best position of the particles ($\vec{x}_{pBest_i}$) are calculated. The best particle among the swarm is selected as the $\vec{x}_{Leader}$. The age of the leader is initialized to θ = 0 and the lifespan Θ of the leader is set to an initial value, Θ_0.

Step 2. *Velocity and position updating:* Velocity and position of each particle are updated in accordance with (9) and (7), respectively.

Step 3. *Updating* $\vec{x}_{pBest_i}$ and $\vec{x}_{Leader}$: For particle $i\ (i=1,2\ ,...,N_p)$, if the newly generated position x_i is better than $\vec{x}_{pBest_i}$ then x_i becomes the new $\vec{x}_{pBest_i}$. In addition, if the best position built in this iteration is better than the $\vec{x}_{Leader}$, then the $\vec{x}_{Leader}$ is updated to be the best position in this iteration. In this sense, this step is similar to that of the conventional PSO, but the $\vec{x}_{Leader}$ represents the best solution generated by particles during the leader's lifetime.

Step 4. *Lifespan control*: After the positions of all particles are updated, the leading power of the leader to improve the entire swarm is evaluated. The lifespan Θ is adjusted by a lifespan controller (Chen *et al.* 2013). The age θ of the leader is increased by 1. If the lifespan is exhausted, i.e., θ > Θ go to *Step 5*, otherwise, go to *Step 7*.

Step 5. *Generating a challenger*: A new particle is generated and is used to challenge the leader whose lifespan is exhausted.

Step 6. *Evaluating the challenger:* The leading power of the newly generated challenger is evaluated. If the challenger has enough leading power, it replaces the old leader and becomes the new leader. The age and lifespan of the new leader are initialized to θ = Θ and θ = Θ_0. Otherwise, the old $\vec{x}_{Leader}$ remains unchanged and will continue to lead the swarm.

Step 7. *Termination condition checking*: If the number of fitness function evaluations (NFFEs) or iteration cycles is larger than a predefined NFFE ($NFFE_{\max}$) or maximum number of iteration cycles, the algorithm terminates. Otherwise, go to *Step 2* for a new round of iteration.

According to the above procedure of the ALC-PSO, the aging mechanism mainly involves three tasks viz. a) design of the lifespan controller for adjusting the lifespan of the leader according to its leading power, (b) generation of a new particle to challenge and replace the old leader and (c) use of criterion to decide whether the generated particle can be accepted as a new leader. For elaborate discussions on *Step 4* (life span control), Step 5 (generating a challenger) and *Step 6* (evaluating the challenger), the work of Chen *et al.* (Chen *et al.* 2013) may be referred.

5. Simulation results and discussions

In the present work, ALC-PSO is applied to modified IEEE 30-bus test system for the solution of OPF problem. The line and bus data and the minimum and maximum limits on control variables for the test system have been adapted from (Alsac & Stott 1974; Yuryevich & Wong 1999). The software is written in MATLAB 2008a computing environment and applied on a 2.63 GHz Pentium IV personal computer with 3 GB RAM. The value of $NFFE_{\max}$ is set to 500 for all the test cases. Discussions on simulation results of the present work are presented below. Results of interest are **bold faced** in the respective tables to indicate the optimization capability of the ALC-PSO algorithm. In this study, 30 test runs are performed solve the OPF problem.

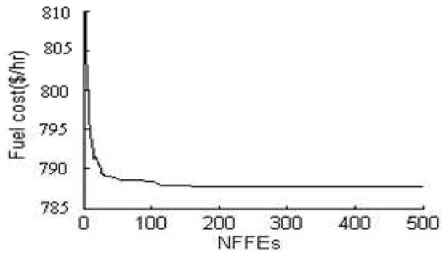

Figure 2. Convergence profile of fuel cost for fuel cost minimization objective of modified IEEE 30-bus system without valve point effect

Table 2. Best Control Variable Settings for Fuel Cost Minimization Objective for Different Techniques

Control variables	Base case	PSO	EGA–DQLF	ALC-PSO
P_{G-1} (p.u.)	NR*	NR*	NR*	0.5160
P_{G-2} (p.u.)	0.80	0.790	0.800	0.7999
P_{G-5} (p.u.)	0.50	0.500	0.500	0.4999
P_{G-8} (p.u.)	0.20	0.350	0.350	0.3499
P_{G-11} (p.u.)	0.20	0.295	0.300	0.2999
P_{G-13} (p.u.)	0.20	0.361	0.400	0.3999
V_1 (p.u.)	1.00	1.000	1.044	1.0500
V_2 (p.u.)	1.00	0.996	1.044	1.0474
V_5 (p.u.)	1.00	0.978	1.025	1.0285
V_8 (p.u.)	1.00	0.980	1.035	1.0360
V_{11} (p.u.)	1.00	1.032	1.070	1.0500
V_{13} (p.u.)	1.00	1.042	1.043	1.0500
T_{6-9} (p.u.)	1.00	0.900	1.038	0.9930
T_{6-10} (p.u.)	1.00	1.000	0.925	0.9406
T_{4-12} (p.u.)	1.00	0.950	0.975	0.9764
T_{28-27} (p.u.)	1.00	0.937	0.975	0.9669
Q_{C-10} (p.u.)	0.00	0.050	0.050	0.0346
Q_{C-12} (p.u.)	0.00	0.050	0.030	0.0054
Q_{C-15} (p.u.)	0.00	0.030	0.000	0.0494
Q_{C-17} (p.u.)	0.00	0.040	0.010	0.0454
Q_{C-20} (p.u.)	0.00	0.050	0.040	0.0179
Q_{C-21} (p.u.)	0.00	0.020	0.020	0.0495
Q_{C-23} (p.u.)	0.00	0.020	0.050	0.0365
Q_{C-24} (p.u.)	0.00	0.060	0.050	0.0498
Q_{C-29} (p.u.)	0.00	0.040	0.050	0.0221
Fuel cost ($/hr)	902.9	956.5	967.86	967.77
P_{Loss} (MW)	6.168	3.629	3.201	**3.1700**
TVD (p.u.)	NR*	NR*	NR*	0.8088
CPU time (s)	NR*	NR*	NR*	10.235

NR* means not reported

5.1 Minimization of fuel cost: optimum control parameter settings of ALC-PSO algorithm are given in TABLE II. A statistical comparison of the simulation results for this objective function of the given test system is reported in TABLE III showing minimum, average and maximum costs as yielded by the comparative optimization algorithms. Figure 2 shows the convergence of minimum fuel cost as yielded by the ALC-PSO approach. The result obtained from the proposed algorithm is compared to the other methods like PSO (. Abido 2002), GSA (Duman 2012) and BBO (Bhattacharya & Chattopadhyay 2011). It may be noted that a fuel cost reduction of **1.452**% (from previous best result of 798.675143 $/h (as reported by GSA in (Duman *et al.* 2012)) to **787.0758** $/h) is accomplished by using the proposed ALC-PSO approach.

Table 3. Comparison of Different OPF Methods for Fuel Cost Minimization Objective

Methods	Fuel cost ($/h)	Simulation

	Minimum	***Average***	***Maximum***	**time (s)**
Gradient Method (Lee *et al.* 1985)	804.85	NR*	NR*	4.32
MDE (Sayah & Zehar 2008)	802.38	802.38	802.40	23.25
Enhanced GA (Bakirtzis *et al.* 2002)	802.06	NR*	802.14	76
Improved GA (Lai & Ma 1997)	800.81	NR*	NR*	NR*
PSO (Abido 2002)	800.41	NR*	NR*	NR*
EADDE (Vaisakh & Srinivas 2011)	800.20	800.24	800.28	3.32
EADHDE (Vaisakh & Srinivas 2011(a))	800.16	NR*	NR*	NR*
DE (Ela *et al.* 2010)	799.29	NR*	NR*	NR*
BBO (Bhattacharya & Chattopadhyay 2011)	799.12	799.19	799.21	11.02
GSA (Duman *et al.* 2012)	798.68	798.91	799.03	10.76
ALC-PSO	**787.08**	788.45	789.57	10.46

NR* means not reported

5.2 Minimization of transmission loss: proposed approach is applied for minimization of transmission loss as one of the objective function for this test system. The obtained optimal values of control variables yielded by the proposed ALC-PSO method are given in TABLE IV. The results obtained by the proposed ALC-PSO algorithm are compared to those reported in the literature like base case (Kumari & Maheswarapu 2010), PSO (Kumari & Maheswarapu 2010), EGA–DQLF (Kumari & Maheswarapu 2010). The obtained minimum real power loss from the proposed approach is found to be **3.17 MW**. The value of P_{Loss} (MW) yielded by ALC-PSO is **0.0308 MW** (i.e. 0**.962%**) less than compared to EGA–DQLF-based best results of 3.2008 MW reported in (Kumari & Maheswarapu 2010). ALC-PSO based convergence profile of minimum value of P_{Loss} (MW) for this test power system is presented in Figure 3. The proposed ALC-PSO based convergence profile of real power loss for this test system is found to be promising one.

Table 4. Best Control Variable Ssettings for P_{Loss} Minimization Objective for Different Techniques

Control variables	**Base case**	**PSO**	**EGA–DQLF**	**ALC-PSO**
P_{G-1} (p.u.)	NR*	NR*	NR*	0.516
P_{G-2} (p.u.)	0.80	0.791	0.800	0.799
P_{G-5} (p.u.)	0.50	0.500	0.500	0.499
P_{G-8} (p.u.)	0.20	0.350	0.350	0.349
P_{G-11} (p.u.)	0.20	0.295	0.300	0.299
P_{G-13} (p.u.)	0.20	0.361	0.400	0.399
V_1 (p.u.)	1.00	1.000	1.044	1.050
V_2 (p.u.)	1.00	0.996	1.044	1.047
V_5 (p.u.)	1.00	0.978	1.025	1.028
V_8 (p.u.)	1.00	0.980	1.035	1.036
V_{11} (p.u.)	1.00	1.032	1.070	1.050
V_{13} (p.u.)	1.00	1.042	1.043	1.050
T_{6-9} (p.u.)	1.00	0.900	1.038	0.993
T_{6-10} (p.u.)	1.00	1.000	0.925	0.941
T_{4-12} (p.u.)	1.00	0.950	0.975	0.976
T_{28-27} (p.u.)	1.00	0.938	0.975	0.967
Q_{C-10} (p.u.)	0.00	0.050	0.050	0.035
Q_{C-12} (p.u.)	0.00	0.050	0.030	0.005
Q_{C-15} (p.u.)	0.00	0.030	0.000	0.049
Q_{C-17} (p.u.)	0.00	0.040	0.010	0.045
Q_{C-20} (p.u.)	0.00	0.050	0.040	0.018
Q_{C-21} (p.u.)	0.00	0.020	0.020	0.049
Q_{C-23} (p.u.)	0.00	0.020	0.050	0.037
Q_{C-24} (p.u.)	0.00	0.060	0.050	0.049
Q_{C-29} (p.u.)	0.00	0.040	0.050	0.022
Fuel cost ($/hr)	902.9	956.45	967.86	967.77
P_{Loss} (MW)	6.168	3.6294	3.2008	**3.1700**
TVD (p.u.)	NR*	NR*	NR*	0.8088
CPU time (s)	NR*	NR*	NR*	10.235

NR* means not reported

2.3 Minimization of TVD:

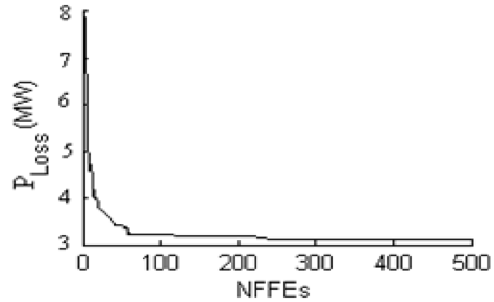

Figure 3. Convergence profile of P_{Loss} for P_{Loss} minimization objective of modified IEEE 30-bus system

The proposed ALC-PSO approach is applied for the minimization of TVD of this test power network. The results yielded by the proposed ALC-PSO are presented in TABLE V. The results obtained by the proposed algorithm are compared to those reported in the literature like DE (Ela *et al.* 2010), BBO (Bhattacharya & Chattopadhyay 2011), and GSA (Duman *et al.* 2012). From this table, **2.218%** improvement in TVD may be recorded by using the proposed ALC-PSO based algorithm (**0.0912 p.u.**) as compared to GSA counterpart (0.093269 p.u.) as reported in (Duman *et al.* 2012). ALC-PSO based convergence profile of TVD (p.u.) for this power system is presented in Figure 4. The proposed ALC-PSO based convergence profile for the TVD minimization objective of this test system is promising one.

Table 5. Best Control Variable Settings for TVD Minimization Objective for Different Techniques

Control variables	**DE**	**BBO**	**GSA**	**ALC-PSO**
P_{G-1} (p.u.)	1.8313	1.7367	1.7332	1.4420
P_{G-2} (p.u.	0.4744	0.4906	0.4926	0.3721
P_{G-5} (p.u.)	0.1873	0.2177	0.2158	0.4309
P_{G-8} (p.u.)	0.1615	0.2327	0.2327	0.1799
P_{G-11} (p.u.)	0.1189	0.1384	0.1377	0.2147
P_{G-13} (p.u.)	0.1651	0.1198	0.1196	0.2720
V_1 (p.u.)	1.0490	1.0185	1.0269	1.0018
V_2 (p.u.)	1.0335	1.0048	1.0099	1.0169
V_5 (p.u.)	1.0117	1.0145	1.0143	1.0185
V_8 (p.u.)	1.0043	1.0092	1.0087	1.0076
V_{11} (p.u.)	1.0432	1.0510	1.0503	1.0066
V_{13} (p.u.)	0.9931	1.0184	1.0163	1.0100
T_{6-9} (p.u.)	1.0439	1.0718	1.0713	1.0090
T_{6-10} (p.u.)	0.9230	0.9000	0.9000	0.9021
T_{4-12} (p.u.)	0.9345	1.0000	0.9965	0.9848
T_{28-27} (p.u.)	0.9616	0.9710	0.9732	0.9619
Q_{C-10} (p.u.)	0.0365	0.0420	0.0414	0.0245
Q_{C-12} (p.u.)	0.0038	0.0370	0.0356	0.0236
Q_{C-15} (p.u.)	0.0409	0.0500	0.0500	0.0500
Q_{C-17} (p.u.)	0.0294	0.0000	0.0000	0.0081
Q_{C-20} (p.u.)	0.0479	0.0500	0.0500	0.0500
Q_{C-21} (p.u.)	0.0447	0.0500	0.0500	0.0487
Q_{C-23} (p.u.)	0.0382	0.0500	0.0500	0.0500
Q_{C-24} (p.u.)	0.0420	0.0500	0.0498	0.0499
Q_{C-29} (p.u.)	0.0126	0.0300	0.0259	0.0205
Fuel cost ($/hr)	805.262	805.758	804.315	852.13
P_{Loss} (MW)	10.441	10.18	9.7659	7.7800
TVD (p.u.)	0.135	0.095	0.0933	**0.0912**
CPU time (s)	NR*	NR*	NR*	10.232

NR* means not reported

4. Conclusions

In this paper, OPF problem is formulated as a nonlinear optimization problem with equality and inequality constraints of the power network. ALC-PSO algorithm has been, successfully, implemented to solve the OPF problem of power system for three individual objectives viz. minimization of fuel cost, real power loss and TVD. The proposed ALC-PSO is tested on modified IEEE 30-bus test systems to demonstrate its effectiveness. The simulation results indicate the robustness and superiority of the proposed approach to solve the OPF problem. The results obtained from the simulation in the present paper obviously demonstrate that the proposed ALC-PSO yields better-quality solution in comparison to other results reported in the recent state-of-the art literature. Thus, the proposed ALC-PSO may be recommended as a very promising algorithm for solving some more complex engineering optimization problems for the future researchers.

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