A Novel Hybrid Optimization Algorithm for Optimal Power Flow with Unified Power Flow Controller

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Abstract—*This paper introduces Particle Swarm Optimization with Differential Perturbed Velocity (PSO-DV) to solve Optimal Power Flow for non-smooth fuel cost functions with Unified power Flow Controller. The proposed algorithm employs a strongly coupled differential operator borrowed from differential evaluation with velocity upgrade function of particle swarm Optimization. The UPFC is a new device from FACTS technology and has great flexibility in control of voltage magnitudes, angle and impedance of the line simultaneously. In this paper the strategic location of UPFC is found using Fuzzy approach by taking voltage magnitudes and voltage stability index(L-Index) as input parameters where L-Index is a real number which gives fair and consistent results for stability among different methods of voltage stability analysis. The control settings of UPFC are determined by PSO-DV. The IEEE-30 bus system is considered to test the feasibility of the proposed method with two objective functions that reflects fuel cost and fuel cost with valve point loading effects. The results shows the effectiveness of the proposed approach and provides better results compared to the existing results of other OPF methods.*

Keywords—OPF, Particle Swarm Optimization, Differential perturbed Velocity, Fuzzy, UPFC, L-Index.

I. INTRODUCTION

Present scenario of Power systems essentially needs Optimal Power Flow (OPF) as a tool for planning and operation. The power flow control and economic operation [1] such as Optimal Power Flow (OPF) including the Flexible Alternating Current Transmission Systems devices has become gaining importance in the power network operation and planning.

Many traditional optimization Techniques existed in literature [2], are Nonlinear Programming (NLP), linear programming (LP) and quadratic programming (QP). The gradient based methods [3] and Newton methods [4] facing the problems while facing inequality constraints. These classical optimization techniques can be applied only when the generating unit fuel cost characteristic are smooth and convex. However, for valve-points and units prohibited operating zones, the characteristics of fuel cost function cannot be illustrated as a smooth, convex function[5]. Recently, many meta-heuristic algorithms, such as Genetic Algorithms(GA)[6] and Tabu search [7], Simulated Annealing[8], Evolutionary Programming[9], and Particle Swarm Optimization [10] have been proposed for solving OPF problem, which does not inflict any limitations on the cost curve shapes. In addition, to improve the search efficiency various hybrid algorithms have been introduced such as hybrid evolutionary programming and tabu search [11] to solve economic dispatch problem with non-smooth cost functions, Hybrid Tabu Search and Simulated Annealing (TS/SA) [12] to solve the problem of OPF with FACTS.

However a new idea of upgrading the velocities of the particles in PSO with a vector differential operator borrowed from the DE was proposed by Das et al. [13]. In this method of particle swarm with differentially perturbed velocity (PSO-DV), the particle velocities are disturbed by a new expression consisting the weighted difference of the position vectors of any two separate particles chosen randomly from the swarm. This differential operator is motivated by the DE mutation mechanism, so it is named as PSO-DV. In the original DE algorithm, the base vector for mutation is chosen at random. In [5], the tournament best vector is chosen as the base vector for mutation operation instead of random vector. Remaining two vectors for mutation are chosen randomly.

Here, an effective PSO-DV approach used to solve the multi-Objective OPF problem with UPFC and Fuzzy approach was used to identify its optimal location. The control settings of series and shunt controllers of UPFC are determined by PSO-DV. The proposed method is examined on IEEE-30 bus system with two objective functions that reflects fuel cost and fuel cost with valve point effects. The proposed Fuzzy-PSODV with UPFC contributes very remarkable results.

1.1 L- Index

In a transmission network consist of 'n' number of buses were 1, 2, 3 ... g; generator buses, and the remaining g+1…….. n load buses. For a given network operating condition, by using Load-flow results, the Voltage-Stability Index [14] is determined as:

$$L_j = \left| 1 - \sum_{i=1}^{g} F_{ji} \frac{v_i}{v_j} \right| \quad .....(1)$$

Where j = g +1,....,n. The values of F_{ji} are complex and are determined from the system Y-bus matrix.

i.e. $F_{LG} = [Y_{LL}]^{-1} [Y_{LG}]^{-1}$ …..(2)

$[Y_{LG}]$ and $[Y_{LL}]$ are the sectionalized parts of Y-bus system matrix. For voltage stability analysis, the Lj value should not be violated the maximum limit of 1 at any load bus j[14].

1.2 Power flow model of UPFC

As a advanced FACTS device UPFC can provide instantaneous control of voltage magnitude, real and reactive power flows. It is well located to overcome most of the issues related to power flow control while improving the considerable transient and dynamic stability. The equivalent circuit of a UPFC power injection model [12] is as shown in Fig.1 with two coordinated synchronous voltage sources represent the UPFC for the purpose of fundamental steady-state analysis, where the voltage sources UPFC are:

$$V_{sh} = V_{sh}(cos\delta_{sh} + jsin\delta_{sh}) \quad ….(3)$$

$$V_{se} = V_{se}(cos\delta_{se} + jsin\delta_{se}) \quad ….(4)$$

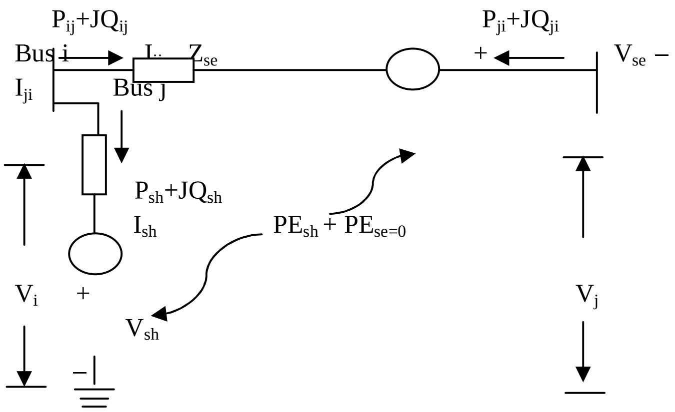

Fig.1:UPFC equivalent circuit

Where, V_{sh}= Voltage magnitude of shunt converter; δ_{sh} =Voltage angle of shunt converter; V_{se}= Voltage magnitude of series converter; and δ_{se}= Voltage angle of series converter. Based on the equivalent circuit and from equations (3) and (4), the real and reactive power flow expressions are:

$$P_{sh} = V_i^2 g_{sh} - V_i V_{sh}(g_{sh}\cos(\theta_i - \theta_{sh}) + b_{sh}\sin(\theta_i - \theta_{sh}))$$
…(5)

$$Q_{sh} = -V_i^2 b_{sh} - V_i V_{sh}(g_{sh}\sin(\theta_i - \theta_{sh}) + b_{sh}\cos(\theta_i - \theta_{sh})) \quad …(6)$$

$$P_{ij} = V_i^2 g_{ij} - V_i V_j(g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij}) - V_i V_{se}(g_{ij}\cos(\theta_i - \theta_{se}) + b_{ij}\sin(\theta_i - \theta_{se})) \quad ...(7)$$

$$Q_{ij} = -V_i^2 b_{ij} - V_i V_j(g_{ij}\sin\theta_{ij} - b_{ij}\cos\theta_{ij}) - V_i V_{se}(g_{ij}\sin(\theta_i - \theta_{se}) - b_{ij}\cos(\theta_i - \theta_{se})) \quad ...(8)$$

$$P_{ji} = V_j^2 g_{ij} - V_i V_j(g_{ij}\cos\theta_{ji} + b_{ij}\sin\theta_{ji}) + V_j V_{se}(g_{ij}\cos(\theta_j - \theta_{se}) + b_{ij}\sin(\theta_j - \theta_{se})) \quad ...(9)$$

$$Q_{ji} = -V_j^2 b_{ij} - V_i V_j(g_{ij}\sin\theta_{ji} - b_{ij}\cos\theta_{ji}) + V_j V_{se}(g_{ij}\sin(\theta_j - \theta_{se}) - b_{ij}\cos(\theta_j - \theta_{se})) \quad ...(10)$$

where

$g_{sh} + jb_{sh} = 1/Z_{sh}$, $g_{ij} + jb_{ij} = 1/Z_{se}$

$\theta_{ij} = \theta_i - \theta_j$, $\theta_{ji} = \theta_j - \theta_i$

The above power flow equations are used to incorporate UPFC in PSODV based Optimal Power Flow.

II. OPF PROBLEM FORMULATION

The solution of OPF aims to optimize a chosen objective function with best possible tuning of the power network control variables, by satisfying the number of equality and inequality constraints. The OPF problem can be formulated as:

$$\min J(x, u)$$

Subject to: $g(x,u) = 0$

$$h_{min} \le h(x,u) \le h_{max}$$

where J =Objective function to be minimized.

x = vector of dependent variables.

g = Equality constraints and h=operating constraints

u = vector of control variables such as:

1. Voltage magnitude of generators V_G at PV buses.
2. Real power output of generator PG at PV buses excluding at the slack bus PG_1.
3. Tap settings of Transformer T.
4. Shunt VAR compensators.

From the above the vector of control variables can be represented as:

$$u^T = [PG_1 ...PG_{ng}, V_{G1} ...V_{Gng}, Qc_1 ...Qc_{nc}, T_1 ...T_{nt}]$$

where, nt= No. of the tap changing transformers and nc= No. of VAR compensators.

The UPFC is located to minimize the selective objective functions and enhance the system performance while, while maintaining thermal limits and voltage constraints. The OPF problem after placing the UPFC can be formulated with the following two objective functions:

2.1 Smooth cost function using quadratic form:

The objective function '*f*' is the total operating fuel cost expressed as:

The objective function = min(*f*)

$$f_1=[\sum_{i=1}^{N_G}(a_iP_{Gi}^2+b_iP_{Gi}+C_i)] \quad \ldots (11)$$

Where, NG=Number of generating units, P_{Gi}= Generation of active power of i[th] generator, a_i, b_i and c_i are the cost coefficients of the i[th] generator.

The comprehensive objective function by imposing the constraints is

$$f_1=[\sum_{i=1}^{N_G}(a_iP_{Gi}^2+b_iP_{Gi}+C_i)]+KP(P_{G1}-P_{G1}^{lim})^2 +KV\sum_{i=1}^{NL}(V_i-V_i^{lim})^2+KQ\sum_{i=1}^{N}(Q_{G,i}-Q_{G,i}^{lim})^2+ KS\sum_{i=1}^{nl}abs(S_i-S_i^{lim})^2+KL\sum_{j=1}^{NL}(L_j-L_j^{lim})^2 \ldots (12)$$

Where KP,KV,KQ,KS and KL are the penalty factors.

NL=No. of PQ buses, nl=No. of transmission lines and Y^{lim} = limiting values dependent variable given as:

$$Y^{lim}== \begin{cases} Y^{max}; & Y > Y^{max} \\ Y^{min}; & Y < Y^{min} \end{cases} \quad \ldots (13)$$

2.2 Non-smooth Cost Function with Valve-Point Loading Effects:

A sine component is included into the cost of the generating units to apply the valve point loading effects which can be represented as:

$$f_2=\sum_{i=1}^{N_G}(a_iP_{gi}^2+b_{gi}+c_i)+\left|d_i\sin\left(e_i(P_{gi}^{min}-P_{gi})\right)\right| +KP(P_{G1}-P_{G1}^{lim})^2+KV\sum_{i=1}^{NL}(V_i-V_i^{lim})^2+KQ\sum_{i=1}^{N}(Q_{G,i}-Q_{G,i}^{lim})^2+KS\sum_{i=1}^{nl}abs(S_i-S_i^{lim})^2+KL\sum_{j=1}^{NL}(L_j-L_j^{lim})^2 \quad \ldots (14)$$

Where, d_i and e_i are the cost coefficients of the generators with valve-point loading.

The minimization problem is treated under the following two categories of constraints:

2.3 Equality Constraints: These are the set of nonlinear load flow expressions that regulate the power systems, i.e.

$$P_{Gi}-P_{Di}-\sum_{j=1}^{n}|V_i||V_j||Y_{ij}|\cos(\theta_{ij}-\delta_i+\delta_j)=0 \quad \ldots (15)$$

$$Q_{Gi}-Q_{Di}+\sum_{j=1}^{n}|V_i||V_j||Y_{ij}|\sin(\theta_{ij}-\delta_i+\delta_j)=0 \quad \ldots (16)$$

where, P_{Gi} and Q_{Gi} are the real and reactive power injected at bus-i respectively, P_{Di} and Q_{Di} are the load demand at i[th] bus, and $|Y_{ij}|$ are the elements of bus admittance matrix.

2.4 Inequality Constraints: The power network operational and security limits are represented as the set of inequality constraints, i.e.

1). Generators real and reactive power outputs.

$$P_{Gi}^{min}\le P_{Gi}\le P_{Gi}^{max}, i=1,2,\ldots\ldots,N_G \quad \ldots (17)$$

$$Q_{Gi}^{min}\le Q_{Gi}\le Q_{Gi}^{max}, i=1,2,\ldots\ldots,N_G \quad \ldots (18)$$

2). Voltage magnitudes of each bus

$$V_i^{min}\le V_i\le V_i^{max}, i=1,2,\ldots\ldots,N \quad \ldots (19)$$

3). Tap settings of Transformer

$$T_i^{min}\le T_i\le T_i^{max}, i=1,2,\ldots\ldots,N_T \quad \ldots (20)$$

4). VAR injections by capacitor banks

$$Q_{Ci}^{min}\le Q_C\le Q_{Ci}^{max}, i=1,2,\ldots\ldots,C_S \quad \ldots (21)$$

5). Loading on Transmission lines

$$S_i\le S_i^{max}, i=1,2,\ldots\ldots,N_L \quad \ldots (22)$$

6). Voltage stability index

$$Lj_i\le Lj_i^{max}, i=1,2,\ldots\ldots,N_{LD} \quad \ldots (23)$$

2.5 UPFC constraints:

UPFC Series injected voltage limits :

$$V_{se\,min}\le V_{se}\le V_{se\,max} \quad \ldots (24)$$

$$\theta_{se\,min}\le \theta se\le \theta_{se\,max} \quad \ldots (25)$$

UPFC Shunt injected voltage limits :

$$V_{sh\,min}\le V_{sh}\le V_{sh\,max} \quad \ldots (26)$$

$$\theta_{sh\,min}\le \theta sh\le \theta_{sh\,max} \quad \ldots (27)$$

The above constraints are controlled using PSO-DV technique which is discussed in subsequent section.

III. CANONICAL PSO AND ITS DRAWBACKS

In PSO, a population of particles are initialized with Y_i, V_i as random positions and velocities respectively. The fitness function '*f*' is calculated using the particles positional coordinates as input variables. The velocity and position upgrade expressions of d[th] dimension of the i[th] particle is:

$$V_{id}(k+1)=\omega.V_{id}(k)+C_{1.}\varphi 1.(P_{lid}-Y_{id})+ C_{2.}\varphi_2.(P_{gid}-Y_{id}) \quad \ldots (28)$$

$$Y_{id}(k+1)=Y_{id}(k)+V_{id}(k+1) \quad \ldots (29)$$

The conventional PSO has been subjected to empherical and theoretical [15] inspections by several researchers. The convergence is premature in several situations, principally when the swarm takes low inertia weight[16] or coefficient of constriction [15].From the equation 28, if $V_{id}(k)$ is small and if (P_{lid}-Y_{id}) and (P_{gid}-Y_{id}) are very small, V_{id} can't accomplish an appreciable value in the forthcoming generations means that loss of exploration power. This can also happen in the beginning stage of search procedure, if the particle is the global best which causes both (P_{lid}-Y_{id}) and (P_{gid}-Y_{id}) to be zero, and V_{id} gets damped rapidly with the ratio ω. The swarm also suffering from the loss of diversity in later iterations.if P_{lid} and P_{gid} are very close [16].The above drawbacks can be overcome by the proposed hybrid algorithm will be discussed in the next section.

IV. PROPOSED PSO-DV ALGORITHM

In PSO-DV algorithm a differential operator is taken from DE and integrated in the velocity-upgrade strategy of PSO. The operator is invoked on the position vectors of two arbitrarily selected particles but not on their individual best positions. In the proposed algorithm, for each particle i in the swarm, the other two different particles, say j and k ($i \neq j \neq k$), are chosen randomly. The difference vector can be obtained as follows:

$$\vec{\delta_d} = \vec{Y_k} - \vec{Y_j} \qquad \ldots(30)$$

The d[th] dimension velocity upgrade expression of i[th] target particle is:

$$V_{id}(k+1) = \omega . V_{id}(k) + \beta\delta_d + C_{2.}\varphi_2.(P_{gid} - Y_{id})$$

If , rand(0,1)≤ CR

$= V_{id}(k)$; or else ….(31)

Where CR= Crossover probability,

δ_d = difference vector d[th] component and

β= scaling factor between 0 and 1.

The cognitive part of the velocity upgrade expression is changed with the differential operator to generate further exploration capacity. If CR ≤ 1, a number of the velocity components will preserve their previous values. Now, a new trial position Tri is created for the particle by combining the upgraded velocity to the preceding position Y_i:

$$\vec{T_{ri}} = \vec{Y_i}(k) + \vec{V_i}(k+1) \qquad \ldots(32)$$

The particle is positioned at this latest position only if the coordinates of the position gains a superior fitness. Therefore, if the minimum of an 'n' dimensional function $f(\vec{X})$ is required, then the target particle is repositioned as follows:

$$\vec{Y_i}(k+1) = \vec{T_{ri}} \quad \text{if } (f(\vec{T_{ri}}) < f(\vec{Y_i}(k)))$$
$$\vec{Y_i}(k+1) = (\vec{Y_i}(k) \quad \text{otherwise} \qquad \ldots(33)$$

Therefore, each time its velocity is modified, the particle either shift to a superior location in the search space or holds to its preceding position. The recent position of the particle is the best position so far compared to the previous positions. On the other side, unlike the traditional PSO, in the present method, P_{lid} at all times equals Y_{id}. So the cognitive part of the algorithm involving $|P_{lid} - Y_{id}|$ is automatically removed. If the particle is stagnant at any position in the search space then the particle is moved to a random mutation to a new position. This procedure helps run away from local minima and also retain the swarm "moving":

If $((\vec{Y_i}(k) = \vec{Y_i}(k+1) = \vec{Y_i}(k+2) = \ldots\ldots = \vec{Y_i}(k+n))$

And $(f(\vec{Y_i}(k+n)) \neq f^*)$ Then for (r = 1 to n)

$$Y_{ir}(k+n+1) = Y_{MIN} + rand_r(0,1)*(Y_{MAX} - Y_{MIN}) \qquad \ldots(34)$$

Where, f*=Global minimum of the fitness function,

n =Maximum No. of iterations up to which stagnation can be tolerated and (Y_{MAX}, Y_{MIN}) are the permissible bounds of the search space. The flow chart of the proposed algorithm is shown in Fig.2.

V. SIMULATION RESULTS AND DISCUSSIONS

The bus data and the branch data of IEEE-30 bus system are taken from[17]. The test system consists of six generators interconnected with 41 transmission lines with a total load of 283.4 MWand126.2 MVAR. The shunt VAR compensators are provided at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 as given in [18]. The proposed method is tested in MATLAB computing environment. The Weak nodes in the system are identified using Fuzzy by taking voltage magnitudes and L-Indices are the inputs and corresponding test results of top five weak nodes are tabulated in Table 1.

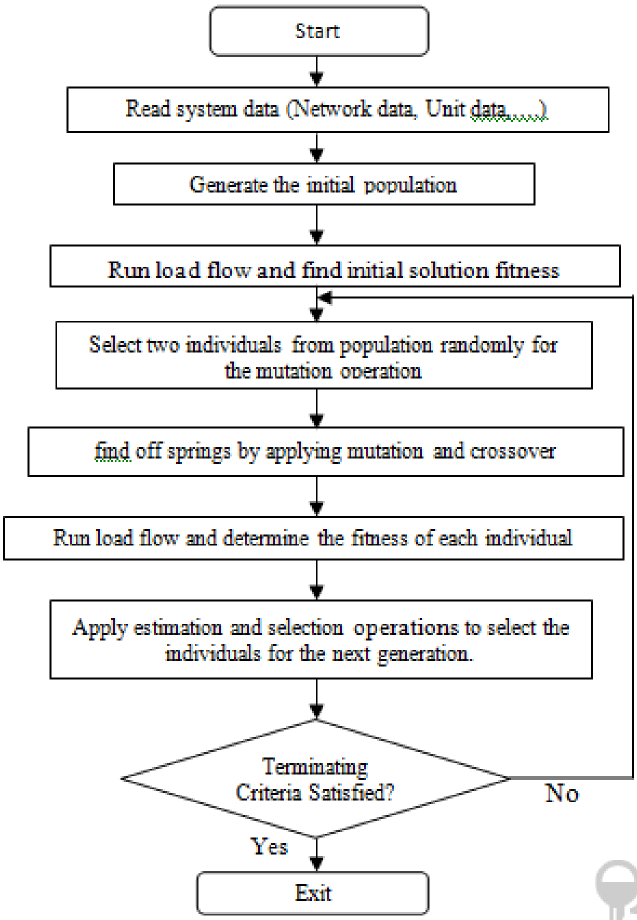

Fig.2:Flow chart of the proposed PSODV with UPFC algorithm.

Table.1:Fuzzy severity of weak nodes.

S.No	Bus No	Severity	Voltage	L-Index	Rank
1	29	45.2197	1.0745	0.1180	1
2	30	39.7756	1.0638	0.1005	2

3	19	39.4556	1.0742	0.0829	3
4	27	38.3695	1.0929	0.0753	4
5	15	36.8125	1.0770	0.0636	5

From the Table.1 the bus 29 has maximum severity considered as weakest node in the system and ranked according to the severity. The line between 29-30 is selected as most favorable location of UPFC. The parameter settings of PSO-DV are shown in Table.2. The PSODV-OPF results of the system after with UPFC for fuel cost and fuel cost with valve point effects are shown in Table.3 and Table.4 respectively.

Table.2: Parameter settings of PSO-DV.

Parameter	Setting value
Size of Population	50
No.of iterations	150
Acceleration Constant(C_2)	2
Mutation Constant(F)	0.1
Crossover Constant(CR)	0.8
Slack bus real power Penalty factor (P_{G1})	1000
Reactive power Penalty factor (KG)	1000
Voltage magnitudes Penalty factor (KV)	10,000
Transmission line loadings Penalty factor (KS)	1000
Voltage stability index Penalty factor (KL)	1000

Table.3: Comparison of PSODV& PSODVUPFC results

Parame Ter	LIMITS MIN	PSO	PSO-DV	PSO-DV
P_{G1}	0.5	1.7766	1.7688	1.771
P_{G2}	0.2	0.4881	0.4844	0.4886
P_{G5}	0.1	0.2272	0.2149	0.2124
P_{G8}	0.1	0.1000	0.1212	0.115
P_{G11}	0.1	0.2127	0.2137	0.2141
P_{G13}	0.12	0.1200	0.1200	0.1200
VG_1	0.95	1.0833	1.0829	1.1000
VG_2	0.95	1.0634	1.0667	1.0858
VG_5	0.95	1.0337	1.0442	1.0672
VG_8	0.95	1.0167	1.0161	1.017
VG_{11}	0.95	1.0297	1.0341	1.0597
VG_{13}	0.95	1.0605	1.0829	1.0718
T_{11}	0.9	1.0322	1.0469	1.0456
T_{12}	0.9	1.0026	1.0240	1.0455
T_{15}	0.9	0.982	0.9642	1.0537
T_{36}	0.9	0.9526	0.9396	1.0304
Q_{C10}	0.0 0.2	0.1633	0.2000	0.000
Q_{C12}	0.0 0.2	0.0550	0.1305	0.0001
Q_{C15}	0.0 0.2	0.1323	0.0448	0.056
Q_{C17}	0.0 0.2	0.1052	0.0567	0.0609
Q_{C20}	0.0 0.2	0.0335	0.0470	0.0400
Q_{C21}	0.0 0.2	0.0115	0.1445	0.0764
Q_{C23}	0.0 0.2	0.0431	0.0000	0.000
Q_{C24}	0.0 0.2	0.0000	0.0340	0.0423
Q_{C29}	0.0 0.2	0.0123	0.0000	0.0761
Cost ($/h)		800.58	800.16	799.34
P_{loss} (P.u)		0.0907	0.0890	0.0871
L_i^{max}	0.0 0.5	0.1423	0.1360	0.1303
VD		1.1890	0.895	0.8181
V_{se}	0.0 0.2			0.0519
V_{sh}	0.9 1.1			0.9854

From the above Table.3, It is observed that the optimal fuel cost in proposed method is reduced to 799.343 $/h compared to PSO and PSO-DV is 800.58$/h and 800.166$/h respectively and the corresponding convergence characteristics of the fuel cost curves are shown in Fig.3. It is also observed that, the L-Index value is reduced to 0.1303 compared to PSO and PSO-DV is 0.1423 and 0.1360 respectively which indicates enhanced voltage stability and the corresponding graphical representations are shown in Fig.4. The voltage deviation also reduced to 0.8181 where as for PSO and PSODV is 1.1890 and 0.895 respectively and the power loss also reduced to 0.0871 p.u from 0.0907 and 0.0890 respectively. The variations of voltage magnitudes of PSO, PSO-DV and PSO-DV with UPFC are shown in Fig.5.

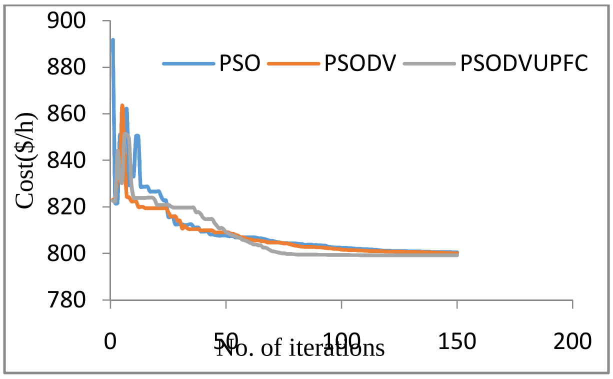

Fig.3:Optimal fuel cost versus No.of iterations.

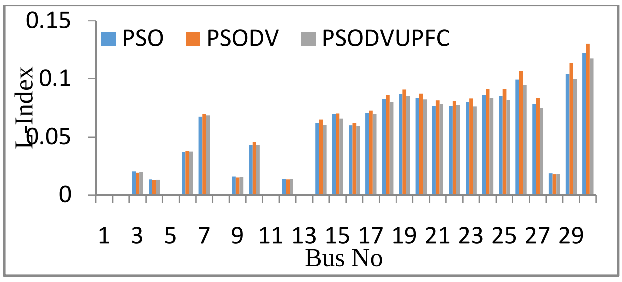

Fig.4: Comparison of L-Indices for different OPF methods.

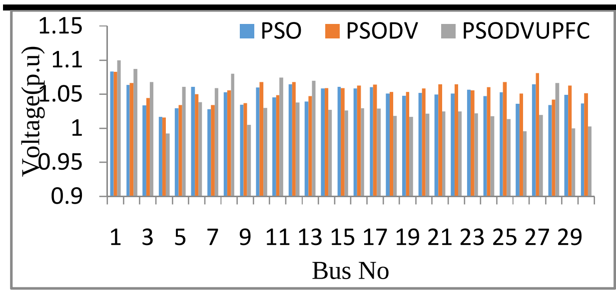

Fig.5: Comparison of voltage magnitudes for different OPF methods.

From the below Table.4,It is observed that the optimal fuel cost in proposed method is reduced to 930.037 $/h compared to PSO and PSO-DV is 952.101$/h and 931.374$/h respectively. It is also observed that, the L-Index value is reduced to 0.1110 compared to PSO and PSO-DV is 0.1227 and 0.1150 respectively which indicates enhanced voltage stability. The voltage deviation also reduced to 1.5756 where as for PSO and PSODV is 1.7688 and 1.0195 respectively.

Table.4: Comparison of PSODV& PSODVUPFC results.

Parame Ter	LIMITS MIN	PSO	PSO DV	PSO-DV
P_{G1}	0.5	1.9719	1.9761	1.9801
P_{G2}	0.2	0.3965	0.3988	0.4071
P_{G5}	0.1	0.1875	0.1897	0.1804
P_{G8}	0.1	0.1130	0.1004	0.1000
P_{G11}	0.1 0.5	0.1500	0.1500	0.1500
P_{G13}	0.12	0.1200	0.1200	0.1200
VG_1	0.95	1.0750	1.0977	1.0971
VG_2	0.95	1.0519	1.0750	1.0739
VG_5	0.95	1.0283	1.0583	1.0546
VG_8	0.95	1.0812	1.0485	1.0231
VG_{11}	0.95	1.0204	1.0484	1.0297
VG_{13}	0.95	1.1000	1.0897	1.0738
T_{11}	0.9	0.9000	1.0035	1.0063
T_{12}	0.9	1.0403	1.0408	1.0679
T_{15}	0.9	0.9972	1.0151	1.0173
T_{36}	0.9	0.9238	0.9604	1.0163
Q_{C10}	0.0 0.2	0.0003	0.0000	0.0018
Q_{C12}	0.0 0.2	0.0000	0.1732	0.1837
Q_{C15}	0.0 0.2	0.0324	0.0693	0.0297
Q_{C17}	0.0 0.2	0.1008	0.2000	0.1458
Q_{C20}	0.0 0.2	0.0000	0.0635	0.0362
Q_{C21}	0.0 0.2	0.0767	0.1103	0.0792
Q_{C23}	0.0 0.2	0.0286	0.0000	0.0529
Q_{C24}	0.0 0.2	0.0268	0.0000	0.0000
Q_{C29}	0.0 0.2	0.0000	0.0329	0.1453
Cost		952.10	931.37	930.03
P_{loss} (P.u)		0.1049	0.1009	0.1036
L_i^{max}	0.0 0.5		0.1150	0.1110
VD			1.7688	1.0195
V_{se}	0.0 0.2			0.0429
V_{sh}	0.9 1.1			0.9851

VI. CONCLUSIONS

In this paper, the proposed technique called PSO-DV with UPFC has been applied for solving the OPF problem with non-smooth generator fuel cost curves with different equality and inequality constraints. Weak nodes are determined by Fuzzy and UPFC is located close to weakest node which effectively improved the system performance.

The proposed technique used to solves the OPF problem efficiently for the two objective functions and it eliminates the drawbacks canonical PSO. Simulation results shows that the PSO-DV with UPFC outperforms the original PSO-DV algorithm and it is effectively implemented to find the best possible settings of the control variables of the IEEE30-bus system. The comparison of the results shows the proposed method is effective and superior to find remarkable global solutions without any restrictions on the different type of fuel cost curves. The proposed algorithm also improves stability margin and reduces the power loss and voltage deviation.

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