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Reduction of Real Power Loss by Using Double Glow-Worms Swarm Co-Evolution Optimization Algorithm Based Levy Flights

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Abstract: **In this paper, a new double glow-worms swarm co-evolution optimization algorithm based Levy flights (DGLF) is proposed to solve optimal reactive power dispatch problem. According to the dissimilar colours of light emitted by glowworm swarm, a certain amount of glowworm swarm was divided into two groups. Levy flights with higher arbitrariness were introduced into one group. Then the two groups of glowworm swarm search for the optimal solution simultaneously and co-evolution for achieving the global optimization. The proposed DGLF has been tested on standard IEEE 30, IEEE 57 bus test systems and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss.**

***Keywords**:* **Optimal Reactive Power, Transmission loss, Glowworm swarm optimization, Levy flights, double glow-worms swarm co-evolution.**

I. INTRODUCTION

Optimal reactive power dispatch (ORPD) problem is to minimize the real power loss and bus voltage deviation. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the complexity in managing inequality constraints. If linear programming is applied then the input- output function has to be uttered as a set of linear functions which mostly lead to loss of accuracy. The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is proposed to improve the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to solve the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. Inspired by the behaviour of natural glowworm swarm, Glowworm Swarm Optimization (GSO) algorithm which is a novel swarm intelligence algorithm was advanced by Indian scholars Krishnan and Ghose in 2005 years [21, 22]. But the fundamental GSO algorithm has some shortcomings, such as slow convergence, squat precision and trouble-free to fall into local optimization. Based the examination of defects in the fundamental GSO algorithm, this algorithm was improved and the Levy flights [23-26] was used in it, so double glow-worms swarm co-evolution optimization algorithm based Levy flights was presented to solve

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optimal reactive power problem. The proposed algorithm DGLF has been evaluated in standard IEEE 30 and IEEE 57, bus test systems. The simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

II. PROBLEM FORMULATION

The optimal power flow problem is treated as a general minimization problem with constraints, and can be mathematically written in the following form:

Minimize f(x, u) (1)

subject to g(x,u)=0 (2)

and

$h(x,u) \leq 0$ (3)

Where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \quad (4)$$

The control variables are the generator bus voltages, the shunt capacitors/reactors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \quad (5)$$

or

$$u = \left(V_{g1}, \ldots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \quad (6)$$

Where ng, nt and nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

III. OBJECTIVE FUNCTION

1.1 Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (7)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (8)$$

where g_k : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

1.2 Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (9)$$

Where ω_v: is a weighting factor of voltage deviation.

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VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \qquad (10)$$

1.3 Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \qquad (11)$$

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

1.4 Inequality Constraints

The inequality constraints h(x,u) reflect the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \qquad (12)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \qquad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \qquad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \qquad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \qquad (16)$$

Where N is the total number of buses, N_T is the total number of Transformers; N_c is the total number of shunt reactive compensators.

IV. BASIC GLOWWORM SWARM OPTIMIZATION ALGORITHM

In the fundamental GSO algorithm, a swarm of glow-worms are arbitrarily dispersed in the explore space of object functions. Accordingly, these glow-worms bear a luminescent quantity called Lucifer in along with them and they have their own decision domain $r_d^i = (0 < r_d^i \le r_s)$.The glow-worms produce light which intensity is proportional to the linked Lucifer in and interrelate with other glow-worms within a variable neighbourhood. The glow-worms' Lucifer in intensity is correlated to the fitness of their existing locations. The superior the intensity of Lucifer in, the better the location of glowworm, in other words, the glowworm symbolizes a good target value. Otherwise, the target value is poor. A glow-worm i consider another glow-worms j as its neighbour if j is within the neighbourhood range of i and the Lucifer in level of j is higher than that of i. In particular, the neighbourhood is defined as a local-decision domain that has a changeable neighbourhood range r_d^i bounded by a radial sensor range $r_s(0 < r_d^i \le r_s)$. Every glowworm selects, using a probabilistic mechanism, a neighbour that has a Lucifer in value higher than its own and moves toward it. That is, glow-worms are fascinated by neighbours that glow brighter. In addition, the dimension of the neighbourhood range of each glowworm is influenced by the amount of glow-worms in the neighbourhood range. The neighbourhood range of the glowworm is relative to the density of its neighbours. If the neighbourhood range covers low density of glow-worms, the

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neighbourhood range will be increased. On the converse, the neighbourhood range will be reduced. In petite, GSO algorithm includes four stages: the primary distribution of glow-worms, Lucifer in-update phase, Movement-phase, Neighbourhood range update.

1.5 The primary distribution of glow-worms phase

The primary distribution of glow-worms phase, in other words, it is begin phase. Reason is to make the glow-worms arbitrarily distribute in the explore space of object functions. Accordingly, these glow-worms carry the same intensity Lucifer in and they have the same decision domain r0.

1.6 Lucifer in-update phase

The glow-worms' Lucifer in intensity is associated to the fitness of their existing locations. The superior the intensity of Lucifer in, the enhanced the location of glowworm, in other words, the glowworm represents a high-quality target value. Or else, the target value is poor. In the algorithm of each iteration procedure, all the glow-worms' position will change, and then the Lucifer in value also follows updates. At time t, the location of the glow-worms i is $x_i(t)$, corresponding value of the objective function at glow-worms i's location at time t is $J(x_i(t))$, put the $J(x^i(t))$ into the $l_i(t)$. $l_i(t)$ Represents the Lucifer in level associated with glow-worms i at time t. The formula as follows:

$$l_i(t) = (1-\rho)l_i(t-1)+\gamma\, J(x_i(t)) \qquad (17)$$

where ρ is the Lucifer in decay constant ($0 < \rho < 1$), γ is the Lucifer in enhancement constant.

1.7 Movement-phase

At the movement phase, each glowworm chooses a neighbour and then shifts toward it with a certain probability. As the glow-worms i's neighbour need to meet two requirements: one, the glowworm within the decision domain of glow-worms i; two, the Lucifer in value is larger than the glow-worms i's. Glow-worms i moves toward a neighbour j which comes from $N_i(t)$ with a certain probability, the probability is $p_{ij}(t)$. Using the formula (18) calculates it:

$$P_{ij}(t) = \frac{l_j(t)-l_i(t)}{\sum_{k\in N_{i(t)}} l_k(t)-l_i(t)} \qquad (18)$$

Glow-worms i after moving, then the location is updated, the location update formula is:

$$x_i(t+1) = x_i(t) + st^* \left(\frac{x_j(t)-x_i(t)}{\|x_j(t)-x_i(t)\|}\right) \qquad (19)$$

where st is the step size.

1.8 Neighbourhood range update phase

With the glow-worm's position updating, it neighbourhood range also pursue update. If the neighbourhood range covers little density of glow-worms, the neighbourhood range will be increased. On the converse, the neighbourhood range will be reduced. The formula of neighbourhood range update as follows:

$$r_d^i(t+1) = min\left\{r_s, max\left\{0, r_d^i(t) + \beta(n_t - |N_i(t)|)\right\}\right\} \qquad (20)$$

where β is a constant parameter and n_t is a parameter used to control the number of neighbours.

In the present model of GSO algorithm [27], each glowworm, according to the Lucifer in value, decides to shift toward a neighbour that has a Lucifer in value higher than its own. Finally, glow-worms are attracted to neighbours with glow brighter. Glow-worms search for the glowworm with the brightest light through moving toward it. In the present GSO algorithm, glow-worms search in a certain area. If there are a lot of glow-worms in the certain area, each glowworm have more neighbours which can augment the number of glow-worms that the glow-worms must be researched. This can result in having more time to search for the optimal solution, that is, slow convergence. If there are petite glow-worms in the certain area, each glowworm has petite neighbours which lead to insufficient among glow-worms and not timely collaboration and easy to fall into local optimization. That is low precision. In nature, glow-worms produce a luminescence through releasing Lucifer in. There are different kinds of glow-worms. Because of this, different kinds of glow-worms emit different colours of light. The yellow and green colours are usually seen. The glow-worms with same colour shift toward each others. In the present model of GSO algorithm, this phenomenon is not considered. Based on this, the scheme that double glowworm swarm was used. In the Cuckoo Search algorithm, in order to augment the arbitrariness of Cuckoo searching the optimal solution, Cuckoo uses a specified flight way that with superior randomness-Levy flights. This flight mode greatly enhanced the arbitrariness of Cuckoo searching the optimal solution. In this paper, Levy flights is applied in the double glowworm swarm, so the double glowworm swarm co-evolution optimization algorithm based Levy flights (DGLF) was presented to solve optimal reactive power dispatch problem .

V. LEVY FLIGHTS

Levy flight [28] is a rank of non-Gaussian random processes whose arbitrary walks are drawn from Levy stable distribution. This allocation is a simple power-law formula $L(s) \sim |s|^{-1-\beta}$ where $0 < \beta < 2$ is an index. Mathematically exclamation, a easy version of Levy distribution can be defined as [29], [30]:

$$L(s,\gamma,\mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} & exp\left[-\frac{\gamma}{2(s-\mu)}\right]\frac{1}{(s-\mu)^{3/2}} \quad if\ 0 < \mu < s < \infty \\ 0 \quad if\ s \le 0 \end{cases} \qquad (21)$$

where $\gamma > 0$ parameter is scale (controls the scale of distribution) parameter, μ parameter is location or shift parameter. In general, Levy distribution should be defined in terms of Fourier transform

$$F(k) = exp\left[-\alpha|k|^{\beta}\right], 0 < \beta \le 2, \qquad (22)$$

where α is a parameter within [-1,1] interval and known as scale factor. An index of o stability $\beta \in [0, 2]$ is also referred to as Levy index. In particular, for $\beta = 1$, the integral can be carried out analytically and is known as the Cauchy probability distribution. One more special case when $\beta= 2$, the distribution correspond to Gaussian distribution. β and α parameters take a key part in determination of the distribution. The parameter β controls the silhouette of the probability distribution in such a way that one can acquire different shapes of probability distribution, especially in the tail region depending on the parameter β. Thus, the smaller β parameter causes the distribution to make longer jumps since there will be longer tail [31-33]. It makes longer jumps for smaller values whereas it makes shorter jumps for bigger values. By Levy flight, new-fangled state of the particle is designed as

$$X^{t+1} = X^t + \alpha \oplus Levy\ (\beta) \qquad (23)$$

α is the step size which must be related to the scales of the problem of interest. In the proposed DGLF method α is random number for all dimensions of particles.

$$X^{t+1} = X^t + random\ (size(D)) \oplus Levy(\beta) \quad (24)$$

The product $\oplus$ means entry-wise multiplications.

A non-trivial scheme of generating step size s samples are summarized as follows,

$$X^{t+1} = X^t + random\ (size(D)) \oplus Levy(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}}\left(x_j^t - gb\right) \qquad (25)$$

where u and v are drawn from normal distributions. That is

$$u \sim N(0, \sigma_u^2) \quad v \sim N(0, \sigma_v^2) \qquad (26)$$

with

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta) \sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}} \right\}^{1/\beta}, \sigma_v = 1 \qquad (27)$$

Here Γ is standard Gamma function. One of the important points to be considered while performing distribution by Levy flights is the value taken by the β parameter and it substantially affects distribution.

VI. DOUBLE GLOWWORM SWARM CO-EVOLUTION OPTIMIZATION ALGORITHM BASED LEVY FLIGHTS

When we use the GSO algorithm optimize the functions, according to the different colours of light, a certain amount of glowworm swarm is divided into two groups. The glow-worms with yellow luminescence make up a sub-population, the glow-worms with green luminescence make up another sub-population. The two groups of glowworm swarm concurrently search for the optimal solution in the explore time. One group searches the optimal solution according to the way of basic GSO; another group takes the way of Levy flights to get the optimal solution. When reaching a certain number of iterations, the glow-worms of two populations essentially converge to the around of optimal value, then the two populations of glow-worms are seen as two glow-worms. Each glowworm will be seen as the glowworm with the brightest light in the sub-population. Next, one glowworm moves toward another one that has a superior Lucifer in value. This combined way between two populations is cooperative for glow-worms out of local optimum and the speed of convergence will be enhanced greatly. According to this scheme the double glowworm swarm co-evolution optimization algorithm based Levy flights (DGLF) is designed to solve optimal reactive power dispatch problem.

The steps of double glowworm swarm co-evolution optimization algorithm based Levy fights for optimal reactive power problem is described as follows:

Step 1: Begin the population: set dimension is m, the number of glow-worms is $2n$, step size is st, and so on.

Step 2: According to the dissimilar colours of light, a certain amount of glowworm swarm is divided into two groups. The size of sub-population is n.

Step 3: Insertion the two groups of $2n$ glow-worms arbitrarily in the search space of the object function.

Step 4: Using the formula (17) put the $J(x_i(t))$ into the $l_i(t)$. $l_i(t)$ represents the Lucifer in level associated with glow-worms i at time t. $J(x_i(t))$ represents the value of the objective function at glow-worms i's location at time t.

Step 5: Every glowworm chooses a neighbour that has a Lucifer in value superior than its own to make up the $N_i(t)$.

Step 6: Each glowworm using the formula (18) picks a neighbour.

Step 7: The glow-worms of one group move by Levy flights and then using the formula (23) renew the location of the glow-worms.

Step 8: The glow-worms of another group move by fundamental GSO and using the formula (19) update the location of the glow-worms.

Step 9: By means of the formula (20) renew the value of the variable neighbourhood range.

Step 10: choose the glowworm with the brightest light of each sub-population at time t.

Step 11: If attained the specified number of iterations and do not reached the maximum number of iterations, one sub-population move toward another. Or else, execute the step (4).

Step 12: If attained the maximum number of iterations, execute the step (10); or else, execute the step (4).

Step 13: Output the results.

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VII. SIMULATION RESULTS

At first DGLF algorithm has been tested in IEEE 30-bus, 41 branch system. It has a total of 13 control variables as follows: 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. The considered security constraints are the voltage magnitudes of all buses, the reactive power limits of the shunt VAR compensators and the transformers tap settings limits. The variables limits are listed in Table 1.

Table 1: Initial Variables Limits (PU)

Control variables	Min. value	Max. value	Type
Generator: Vg	0.92	1.11	Continuous
Load Bus: VL	0.94	1.00	Continuous
T	0.94	1.00	Discrete
Qc	-0.11	0.31	Discrete

The transformer taps and the reactive power source installation are discrete with the changes step of 0.01. The power limits generators buses are represented in Table 2. Generators buses are: PV buses 2,5,8,11,13 and slack bus is 1.the others are PQ-buses.

Table 2: Generators Power Limits in MW and MVAR

Bus n°	Pg	Pgmin	Pgmax	Qgmin
1	98.00	51	202	-21
2	81.00	22	81	-21
5	53.00	16	53	-16
8	21.00	11	34	-16
11	21.00	11	29	-11
13	21.00	13	41	-16

Table 3: Values of Control Variables after Optimization and Active Power Loss

Control Variables (p.u)	DGLF
V1	1.0644
V2	1.0550
V5	1.0312
V8	1.0441
V11	1.0849
V13	1.0651
T4,12	0.01
T6,9	0.00
T6,10	0.91
T28,27	0.90
Q10	0.10
Q24	0.10
PLOSS	4.9185
VD	0.9070

Table 3 show the proposed approach succeeds in keeping the dependent variables within their limits.

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Table 4 summarizes the results of the optimal solution obtained by PSO, SGA and DGLF methods. It reveals the reduction of real power loss after optimization.

Table 4: Comparison Results of Different Methods

SGA[34]	PSO[35]	DGLF
4.98 Mw	4.9262Mw	4.9185 Mw

Secondly the proposed hybrid DGLF algorithm for solving ORPD problem is tested in standard IEEE-57 bus power system. The IEEE 57-bus system data consists of 80 branches, seven generator-buses and 17 branches under load tap setting transformer branches. The possible reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. In this case, the search space has 27 dimensions, i.e., the seven generator voltages, 17 transformer taps, and three capacitor banks. The system variable limits are given in Table 5. The initial conditions for the IEEE-57 bus power system are given as follows:

P_{load} = 12.421 p.u. Q_{load} = 3.305 p.u.

The total initial generations and power losses are obtained as follows:

$\sum P_G$ = 12.7721 p.u. $\sum Q_G$ = 3.4552 p.u.

P_{loss} = 0.27443 p.u. Q_{loss} = -1.2241 p.u.

Table 6 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after DGLF based optimization which are within their acceptable limits. In Table 7, a comparison of optimum results obtained from proposed DGLF with other optimization techniques for ORPD mentioned in literature for IEEE-57 bus power system is given. These results indicate the robustness of proposed DGLF approach for providing better optimal solution in case of IEEE-57 bus system.

Table 5: Variables limits for ieee-57 bus power system (p.u.)

REACTIVE POWER GENERATION LIMITS							
BUS NO	1	2	3	6	8	9	12
Q_{GMIN}	-1.1	-.010	-.01	-0.01	-1.1	-0.02	-0.2
Q_{GMAX}	1	0.1	0.1	0.23	1	0.01	1.50

VOLTAGE AND TAP SETTING LIMITS					
V_{GMIN}	V_{GMAX}	V_{PQMIN}	V_{PQMAX}	T_{KMIN}	T_{KMAX}
0.5	1.0	0.91	1.01	0.5	1.0

SHUNT CAPACITOR LIMITS			
BUS NO	18	25	53
Q_{CMIN}	0	0	0
Q_{CMAX}	10	5.1	6.0

Table 6: control variables obtained after optimization by DGLF method for ieee-57 bus system (p.u.).

Control Variables	DGLF
V1	1.2
V2	1.060
V3	1.051
V6	1.040
V8	1.061
V9	1.033

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V12	1.043
Qc18	0.0840
Qc25	0.331
Qc53	0.0621
T4-18	1.013
T21-20	1.051
T24-25	0.960
T24-26	0.933
T7-29	1.074
T34-32	0.931
T11-41	1.011
T15-45	1.051
T14-46	0.920
T10-51	1.031
T13-49	1.050
T11-43	0.911
T40-56	0.901
T39-57	0.960
T9-55	0.970

Table 7: comparative optimization results for ieee-57 bus power system (p.u.)

S.No.	Optimization Algorithm	Best Solution	Worst Solution	Average Solution
1	NLP [36]	0.25902	0.30854	0.27858
2	CGA [36]	0.25244	0.27507	0.26293
3	AGA [36]	0.24564	0.26671	0.25127
4	PSO-w [36]	0.24270	0.26152	0.24725
5	PSO-cf [36]	0.24280	0.26032	0.24698
6	CLPSO [36]	0.24515	0.24780	0.24673
7	SPSO-07 [36]	0.24430	0.25457	0.24752
8	L-DE [36]	0.27812	0.41909	0.33177
9	L-SACP-DE [36]	0.27915	0.36978	0.31032
10	L-SaDE [36]	0.24267	0.24391	0.24311
11	SOA [36]	0.24265	0.24280	0.24270

12	LM [37]	0.2484	0.2922	0.2641
13	MBEP1 [37]	0.2474	0.2848	0.2643
14	MBEP2 [37]	0.2482	0.283	0.2592
15	BES100 [37]	0.2438	0.263	0.2541
16	BES200 [37]	0.3417	0.2486	0.2443
17	Proposed DGLF	0.22341	0.23460	0.23117

VIII. CONCLUSION

DGLF algorithm has been effectively applied for ORPD problem. DGLF based ORPD is tested in standard IEEE 30, IEEE 57 bus system. Performance comparisons with well-known population-based algorithms give encouraging results. DGLF emerges to find good solutions when compared to that of other algorithms. The simulation results presented in previous section prove the ability of DGLF approach to arrive at near global optimal solution.

REFERENCES

[1] O.Alsac,and B. Scott, “Optimal load flow with steady state security”,IEEE Transaction. PAS -1973, pp. 745-751.

[2] Lee K Y ,Paru Y M , Oritz J L –A united approach to optimal real and reactive power dispatch , IEEE Transactions on power Apparatus and systems 1985: PAS-104 : 1147-1153

[3] A.Monticelli , M .V.F Pereira ,and S. Granville , “Security constrained optimal power flow with post contingency corrective rescheduling” , IEEE Transactions on Power Systems :PWRS-2, No. 1, pp.175-182.,1987.

[4] Deeb N ,Shahidehpur S.M ,Linear reactive power optimization in a large power network using the decomposition approach. IEEE Transactions on power system 1990: 5(2) : 428-435

[5] E. Hobson ,’Network consrained reactive power control using linear programming, ‘ IEEE Transactions on power systems PAS -99 (4) ,pp 868=877, 1980

[6] K.Y Lee ,Y.M Park , and J.L Oritz, “Fuel –cost optimization for both real and reactive power dispatches” , IEE Proc; 131C,(3), pp.85-93.

[7] M.K. Mangoli, and K.Y. Lee, “Optimal real and reactive power control using linear programming” , Electr.Power Syst.Res, Vol.26, pp.1-10,1993.

[8] C.A. Canizares , A.C.Z.de Souza and V.H. Quintana , “ Comparison of performance indices for detection of proximity to voltage collapse ,’’ vol. 11. no.3 , pp.1441-1450, Aug 1996 .

[9] S.R.Paranjothi ,and K.Anburaja, “Optimal power flow using refined genetic algorithm”, Electr.Power Compon.Syst , Vol. 30, 1055-1063,2002.

[10] D. Devaraj, and B. Yeganarayana, “Genetic algorithm based optimal power flow for security enhancement”, IEE proc-Generation.Transmission and. Distribution; 152, 6 November 2005.

[11] Berizzi, C. Bovo, M. Merlo, and M. Delfanti, “A ga approach to compare orpf objective functions including secondary voltage regulation,” Electric Power Systems Research, vol. 84, no. 1, pp. 187 – 194, 2012.

[12] C.-F. Yang, G. G. Lai, C.-H. Lee, C.-T. Su, and G. W. Chang, “Optimal setting of reactive compensation devices with an improved voltage stability index for voltage stability enhancement,” International Journal of Electrical Power and Energy Systems, vol. 37, no. 1, pp. 50 – 57, 2012.

[13] P. Roy, S. Ghoshal, and S. Thakur, "Optimal var control for improvements in voltage profiles and for real power loss minimization using biogeography based optimization," International Journal of Electrical Power and Energy Systems, vol. 43, no. 1, pp. 830 – 838, 2012.

[14] B. Venkatesh, G. Sadasivam, and M. Khan, "A new optimal reactive power scheduling method for loss minimization and voltage stability margin maximization using successive multi-objective fuzzy lp technique," IEEE Transactions on Power Systems, vol. 15, no. 2, pp. 844 – 851, may 2000.

[15] W. Yan, S. Lu, and D. Yu, "A novel optimal reactive power dispatch method based on an improved hybrid evolutionary programming technique," IEEE Transactions on Power Systems, vol. 19, no. 2, pp. 913 – 918, may 2004.

[16] W. Yan, F. Liu, C. Chung, and K. Wong, "A hybrid genetic algorithminterior point method for optimal reactive power flow," IEEE Transactions on Power Systems, vol. 21, no. 3, pp. 1163 –1169, aug. 2006.

[17] J. Yu, W. Yan, W. Li, C. Chung, and K. Wong, "An unfixed piecewiseoptimal reactive power-flow model and its algorithm for ac-dc systems," IEEE Transactions on Power Systems, vol. 23, no. 1, pp. 170 –176, feb. 2008.

[18] F. Capitanescu, "Assessing reactive power reserves with respect to operating constraints and voltage stability," IEEE Transactions on Power Systems, vol. 26, no. 4, pp. 2224–2234, nov. 2011.

[19] Z. Hu, X. Wang, and G. Taylor, "Stochastic optimal reactive power dispatch: Formulation and solution method," International Journal of Electrical Power and Energy Systems, vol. 32, no. 6, pp. 615 – 621, 2010.

[20] Kargarian, M. Raoofat, and M. Mohammadi, "Probabilistic reactive power procurement in hybrid electricity markets with uncertain loads," Electric Power Systems Research, vol. 82, no. 1, pp. 68 – 80, 2012.

[21] K. N. Krishnand, D. Ghose, Glowworm swarm optimisation for simultaneous capture of multiple local optima of multimodal functions, Swarm Intell, 3, 87-124 (2009).

[22] K. N. Krishnand, D. Ghose, Glowworm swarm optimization: a new method for optimizing multi-modal functions, Int. J.Computational Intellingence Studies, 1, 93-119 (2009).

[23] Xin-She Yang, Suash Deb, Cuckoo Search via L´evy Flights, In: Proc. of World Congress on Nature Biologically Inspired Computing (NaBIC2009), India: IEEE Publications, 210-214(2009).

[24] Barthelemy P., Bertolotti J., Wiersma D. S., A L´evy flight for light, Nature, 453, 495-498 (2008).

[25] Brown C., Liebovitch L.S., Glendon R., L´evy flights inDobe Ju

[26] Yongquan Zhou, Yingju Wang, Sucai He and Jinzhao WuA ,Novel Double Glowworm Swarm Co-Evolution Optimization Algorithm based L´evy FlightsAppl. Math. Inf. Sci. 8, No. 1L, 355-361 (2014).

[27] K. N. Krishnand, D. Ghose, Detection of multiple source locations using a glowworm metaphor with applications to collective robotics. In proceeding of IEEE swarm intelligence symposium, Piscataway: IEEE press, 84-91 (2005).

[28] V. Chechkin, R. Metzler, J. Klafter, and V. Y. Gonchar, "Introduction To The Theory Of Lévy Flights," in R. Klages, G. Radons, and I. M. Sokolov (Eds.), Anomalous Transport: Foundations and Applications, John Wiley & Sons, pp. 129-162, 2008.

[29] X.-S.Yang and S. Deb, "Multiobjective cuckoo search for design optimization," Computers & Operations Research.

[30] X.-S. Yang, Engineering Optimization An Introduction with Metaheuristic Applications, first ed., New Jersey: John Wiley and Sons, 2010.

[31] C.-Y. Lee and X. Yao, "Evolutionary Algorithms with Adaptive Levy Mutations," in Proc. the 2001 Congress on Evolutionary Computation,Seoul, South Korea, 2001, pp. 568-575.

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Vol. 1, Issue 1, pp: (1-12), Month: September-December 2014, Available at: www.noveltyjournals.com

[32] Hüseyin Hakli and Harun Uğuz, "Levy Flight Distribution for Scout Bee in Artificial Bee Colony Algorithm" Lecture Notes on Software Engineering, Vol. 1, No. 3, August 2013.

[33] W. Xiang and M. An, "An efficient and robust artificial bee colony algorithm for numerical optimization," Computers & Operations Research, In Press, 2012.

[34] Q.H. Wu, Y.J.Cao, and J.Y. Wen. Optimal reactive power dispatch using an adaptive genetic algorithm. Int. J. Elect. Power Energy Syst. Vol 20. Pp. 563-569; Aug 1998.

[35] B. Zhao, C. X. Guo, and Y.J. CAO. Multiagent-based particle swarm optimization approach for optimal reactive power dispatch. IEEE Trans. Power Syst. Vol. 20, no. 2, pp. 1070-1078, May 2005.

[36] Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang, "Seeker optimization algorithm for optimal reactive power dispatch," IEEE Trans. Power Systems, Vol. 24, No. 3, August 2009, pp. 1218-1231.

[37] J. R. Gomes and 0. R. Saavedra, "Optimal reactive power dispatch using evolutionary computation: Extended algorithms," IEE Proc.-Gener. Transm. Distrib.. Vol. 146, No. 6. Nov. 1999.

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