Decline of Active Power Loss and preservation of Voltage Stability by Hybridization of Cuckoo Search Algorithm with Powell Search

K. Lenin[1*], B.Ravindhranath Reddy[2]

Abstract— In this paper, Hybridization of Cuckoo Search algorithm with Powell Search (HCSPS) is used to solve optimal reactive power problem. Cuckoo search (CS) has been recently projected as a population-based optimization algorithm and it is has so far been efficaciously applied in a variety of fields. The inertia weight of Levy flights is presented to balance the capability of global and local search. The Powell local search method is used to progress the best guesstimate found by the cuckoo search algorithm. The hybridization of cuckoo search algorithm and Powell search technique will deliver a more active trade-off between exploitation and exploration of the search space. The proposed HCSPS has been tested on standard IEEE 57 bus test system and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss.

Keywords—cuckoo search algorithm, Powell search, optimal reactive power, Transmission loss.

I. INTRODUCTION

Reactive power optimization places a significant role in optimal operation of power systems. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been implemented to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the intricacy in managing inequality constraints. The problem of voltage stability and collapse play a key role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is projected to increase the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem.

K.Lenin has received his B.E., Degree, electrical and electronics engineering in 1999 from university of madras, Chennai, India and M.E., Degree in power systems in 2000 from Annamalai University, TamilNadu, India. Presently pursuing Ph.D., degree at JNTU, Hyderabad,India.

Bhumanapally. RavindhranathReddy, Born on 3rd September,1969. Got his B.Tech in Electrical & Electronics Engineering from the J.N.T.U. College of Engg., Anantapur in the year 1991. Completed his M.Tech in Energy Systems in IPGSR of J.N.T.University Hyderabad in the year 1997. Obtained his doctoral degree from JNTUA,Anantapur University in the field of Electrical Power Systems. Published 12 Research Papers and presently guiding 6 Ph.D. Scholars. He was specialized in Power Systems, High Voltage Engineering and Control Systems. His research interests include Simulation studies on Transients of different power system equipment.

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 elucidate 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 calculate 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. This paper present's Hybridization of Cuckoo Search algorithm with Powell Search (HCSPS) to solve optimal reactive power problem. Cuckoo search (CS) algorithm [21-25] has been freshly developed as a meta-heuristics population based optimization method. This algorithm is based on parasitic behaviour of some cuckoo species in amalgamation with the Levy flight behaviour of some birds and fruit flies. Although the CS algorithm is noble at exploring the search space and locating the region of global minimum, it is sluggish at exploiting the solutions. The hybridization of CS algorithm and Powell direct search method will deliver a more active trade-off between exploitation and exploration of the search space. The proposed HCSPS algorithm has been evaluated on standard IEEE 57, bus test system. 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 considered as a common minimization problem with constraints, and can be written in the following form:

$$\text{Minimize } f(x, u) \tag{1}$$

$$\text{Subject to } g(x,u)=0 \tag{2}$$

and

$$h(x, u) \leq 0 \tag{3}$$

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 and the transformers tap-settings:

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

or

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

Where Ng, Nt and Nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

III. Objective Function

A. Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be mathematically 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.

B. 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.

VD is the voltage deviation given by:

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

C. 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:

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

D. Inequality Constraints

The inequality constraints h(x,u) imitate 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:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad (12)$$

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

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (15)$$

Upper and lower bounds on the compensators reactive powers:

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

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. Cuckoo Search Algorithm

The cuckoo Search (CS) was enthused by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of host birds. Some cuckoos have evolved in such a way that female parasitic cuckoos can emulate the colors and patterns of the eggs of a few chosen host species. In general, the cuckoo eggs hatch marginally earlier than their host eggs. Once the first cuckoo chick is hatched, his first nature action is to evict the host eggs by dimly propelling the eggs out of the nest. The CS models such breeding behavior and, thus, can be applied to various optimization problems. The performance of the CS can be improved by using Lévy Flights instead of simple arbitrary walk.

A. Lévy Flights

In nature, animals hunt for food in an arbitrary or quasi arbitrary manner. Commonly, the foraging path of an animal is effectually an arbitrary walk because the next move is based on both the current location and the changeover probability to the next location. The preferred direction covertly depends on a probability, which can be modeled mathematically. Various studies have shown that the flight behavior of many animals and insects demonstrates the typical characteristics of Lévy flights. A Lévy flight is an arbitrary walk in which the step-lengths are dispersed according to a heavy-tailed probability distribution. After a large number of steps, the distance from the origin of the arbitrary walk tends to a stable distribution.

B. Cuckoo Search Implementation

Each egg in a nest characterizes a solution, and a cuckoo egg epitomizes a new solution. The goal is to employ the new and hypothetically better solutions (cuckoos) to replace not-so-good solutions in the nests. In the simplest form, each nest has one egg. The CS is based on three idealized rules:

(i)Each cuckoo lays one egg at a time, and dumps it in a arbitrarily chosen nest.

(ii)The best nests with high class of eggs (solutions) will carry over to the next generations.

(iii)The number of available host nests is fixed, and a host can determine an alien egg with probability p_a □ [0,1] In this case, the host bird can either throw the egg away or abandon the nest to build a entirely new nest in a new location.

For uncomplicatedness, the last assumption can be approximated by a fraction p_a of the n nests being replaced by new nests, having new arbitrary solutions. Based on the above-mentioned rules, the basic steps of the CS algorithm can be summarized as follows,

Begin

Objective function f(x), x = $(x_{1,\ldots\ldots,} x_d)^T$
Produce initial population of n host nests x_i , (i = 1,2,..,n)
While (t Max Generation) or (stop criterion)
Get a cuckoo arbitrarily by Lévy flights
Estimate its fitness F_i
Pick a nest among n (say.j) randomly
If ($F_i > F_j$) substitute j by the new solution;
End if
A fraction (p_a) of worse nests is abandoned and new ones are built;
Keep the best solutions (or nests with quality solutions);
Rank the solutions and find the current best
End while
Post process results and visualization
End

When generating new solutions $x_i(t+1)$for the ith cuckoo, the following Lévy flight is performed

$$x_i(t+1) = x_i(t) + \alpha \,\Theta\, Levy\,(\lambda) \qquad (17)$$

where α > 0 is the step size, which should be related to the scale of the problem of interest. The product Θ means entry-wise multiplications.

In this research work, we consider a Lévy flight in which the step-lengths are distributed according to the following probability distribution

$$Levy\; u = t^{-\lambda}, 1 < \lambda \leq 3 \qquad (18)$$

C. Integration of Levy flight with the inertia weight

In CS algorithm, Levy flights are a arbitrary walk whose step length is haggard from the Levy distribution. To balance the global and local ability of CS algorithm, in this work, when producing new solution $x_i(t+1)$ for, say cuckoo i , a Levy flight integrating with the inertia weight, ω_{iter} , which controls the search capability is performed by ,

$$x_i(t+1) = \omega_{iter} \cdot x_i(t) + \alpha \,\Theta\, Levy\,(\lambda) \qquad (19)$$

While presenting the perception of inertia weight ω_{iter} [26] observed that a reasonable choice for ω_{iter} should linearly diminished from a relatively large value to a small value through the course so that the CS algorithm had a improved performance compared with fixed$v\omega_{iter}$ settings. In principle, the larger ω_{iter}has superior global exploration ability whereas the small ω_{iter}has greater local exploration ability. In this study, based on (19), the inertia weight ω_{iter}as a nonlinear function of the present iteration number (*iter*) at each time step. The projected adaptation of ω_{iter} is given as [27]:

$$\omega_{iter} = \omega_{initial} \times u^{-iter} \qquad (20)$$

where $\omega_{initial}$is the initial inertia weight value selected in the range [0,1] and u is a constant value in the range [1.0001,1.005]. In the experiments conducted in [27], u is set to 1.0002 and the performance of the algorithm is evaluated for different values of $\omega_{initial}$. A superior inertia weight facilitates global exploration and a smaller inertia weight tends to enable local exploration to fine-tune the current exploration area.

V. Powell search method

Powell's search is an extension of basic pattern search method. It is based on conjugate direction method and is estimated to speed up the convergence of nonlinear objective functions. A conjugate direction method diminishes a quadratic function in a finite number function. It can be diminished in few steps using Powell's method [28]. In Powell's method [29], the primary step is to set exploration coordinate directions.

$$S_g^h = \begin{cases} 1, g = h \\ 0, g \neq h \end{cases} (g, h = 1,2,..,n) \qquad (21)$$

A step length is arbitrarily generated by implying Eq. (22) to minimize function.

$$\lambda_g^* = \lambda_g^{min} + \left(\lambda_g^{max} - \lambda_g^{min}\right) rand(g = 1,2,..,n) \quad (22)$$

The decision variable X_g is altered once along the coordinate direction (h) as

$$X_g = X_g + \lambda_g^* S_g^h (g = 1,2,..,n) \qquad (23)$$

Decision variable is modernized only if the new value of decision variable optimizes the objective function. This procedure endures for all 'n' coordinate directions. For subsequent cycle of optimization, pattern search direction is obtained as

$$S_g^h = X_g - Z_g(g, h = 1,2,..,n) \qquad (24)$$

In accumulation one of the coordinate directions thrown away in favour of the pattern direction as

$$S_g^m = S_g^h(g = 1,2,..,n; h = n+1) \qquad (25)$$

This procedure endures until all the coordinate directions have been thrown away and entire process will resume again along one of the coordinate direction. Finally, updating process continues until the Powell's method has been reached to maximum set iterations.

VI. Hybridization of Cuckoo Search algorithm with Powell Search

One of the utmost popular constraint handling techniques used with meta-heuristics algorithms has been Stochastic Ranking (SR) [30]. SR adopts a rank selection mechanism that attempts to balance the influence of considering either the objective function value or the degree of violation of the constraints (a parameter called p_f has been adopted for this sake). Thus, the constraint handling technique adopted in this work is the set of SR proposed by Runarsson and Yao [30].Firstly, arbitrarily generation of primary population from the decision space. In each generation, it exploits the property of CS algorithm, and then Powell's pattern search method has been used further augment the performance, by scrutinizing neighbouring solutions. This process is repeated to update the population in each iteration.

Detailed steps of the HCSPS algorithm are given in the following:

Step 1: Arbitrarily produce an initial population from the decision space.

Step 2: Run improved CS algorithm to produce new solutions.
Step 3: Estimate the population based on SR technique, rank the solutions and find the current best of the CS population (best solution so far).
Step 4: Apply the Powell's search method on the current best to progress and update this solution.
Step 5: Check convergence condition. If not satisfied, go to Step 2.

VII. Simulation Results

The proposed HCSPS algorithm for solving Optimal Reactive Power problem is tested for standard IEEE-57 bus power system. The IEEE 57-bus system data consists of 80 branches, 7 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 I. The preliminary conditions for the IEEE-57 bus power system are given as follows:

P_{load} = 12.422 p.u. Q_{load} = 3.335 p.u.

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

$\sum P_G$ = 12.7722 p.u. $\sum Q_G$ = 3.4556 p.u.

P_{loss} = 0.27442 p.u. Q_{loss} = -1.2246 p.u.

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

TABLE I: 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	6.2

TABLE II: CONTROL VARIABLES OBTAINED AFTER OPTIMIZATION BY HCSPS METHOD FOR IEEE-57 BUS SYSTEM (P.U.).

Control Variables	HCSPS
V1	1.1
V2	1.065
V3	1.056
V6	1.047
V8	1.063
V9	1.035
V12	1.046
Qc18	0.0848
Qc25	0.335
Qc53	0.0628
T4-18	1.018
T21-20	1.053
T24-25	0.961
T24-26	0.938
T7-29	1.074
T34-32	0.935
T11-41	1.018
T15-45	1.053
T14-46	0.925
T10-51	1.036
T13-49	1.059
T11-43	0.912
T40-56	0.903
T39-57	0.964
T9-55	0.975

TABLE III: COMPARATIVE OPTIMIZATION RESULTS FOR IEEE-57 BUS POWER SYSTEM (P.U.)

S.No.	Optimization Algorithm	Best Solution	Worst Solution	Average Solution
1	NLP [31]	0.25902	0.30854	0.27858
2	CGA [31]	0.25244	0.27507	0.26293
3	AGA [31]	0.24564	0.26671	0.25127
4	PSO-w [31]	0.24270	0.26152	0.24725
5	PSO-cf [31]	0.24280	0.26032	0.24698
6	CLPSO [31]	0.24515	0.24780	0.24673
7	SPSO-07 [31]	0.24430	0.25457	0.24752
8	L-DE [31]	0.27812	0.41909	0.33177
9	L-SACP-DE [31]	0.27915	0.36978	0.31032
10	L-SaDE [31]	0.24267	0.24391	0.24311
11	SOA [31]	0.24265	0.24280	0.24270
12	LM [32]	0.2484	0.2922	0.2641
13	MBEP1 [32]	0.2474	0.2848	0.2643
14	MBEP2 [32]	0.2482	0.283	0.2592
15	BES100 [32]	0.2438	0.263	0.2541
16	BES200 [32]	0.3417	0.2486	0.2443
17	Proposed HCSPS	0.22346	0.23462	0.23114

VIII. Conclusion

In this paper, the Hybridization of Cuckoo Search algorithm with Powell Search (HCSPS) has been successfully implemented to solve Optimal Reactive Power problem. The efficiency of the proposed HCSPS algorithm has been tested in standard IEEE 57-bus system. The results are compared with other heuristic methods and the proposed HCSPS algorithm demonstrated its effectiveness and robustness in minimization of real power loss and also various system control variables are well within the acceptable limits .

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] A. 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] A. 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] X. Yang and S. Deb, Cuckoo search via Levy flights, Proc. of World Congress on Nature and Biologically Inspired Computing 2009, pp. 210–214.

[22] A. Gandomi, X. Yang, and A. Alavi, Cuckoo search algorithm: a meta-heuristic approach to structural optimization problem, Eng. Comput. 29, 2013, pp. 17–35.

[23] X. Yang, and S. Deb, Multi-objective cuckoo search for design optimization, Comput. Oper. Res. 40, 2013, pp. 1616–1624.

[24] W. Long, X. Liang, Y. Huang and Y. Chen, An effective hybrid cuckoo search algorithm for constrained global optimization, Neural Comput. Appl. 2014, in Press, Doi: 10.1007/s00521- 014-1577-1.

[25] Wen Long, Guizhou University, "Hybrid Cuckoo Search Algorithm based on Powell Search for Constrained Engineering Design Optimization" wseas transactions on mathematics, Volume 13, 2014, pp431-440, 2014.

[26] K. Abdul-Rain, M. Abd-Malek and N. SiewChin, Nature-inspired cuckoo search algorithm for side lobe suppression in a symmetric linear antenna array, Radio-Eng. 21, 2012, pp. 865– 874.

[27] B. Jiao, Z. Lian and X. Gu, A dynamic inertia weight particle swarm optimization algorithm, Chaos Solitons Fractals 37, 2008, pp. 698–705.

[28] S. Rao, Engineering optimization: theory and practice, John Wiely and Sons, New York, 1996

[29] N. Narang, J. Dhillon and D. Kothari, Multiobjective fixed head hydrothermal scheduling using integrated predator-prey optimization and Powell search method, Energy 47, 2012, pp. 237–252.

[30] T.Runarsson and X. Yao, Stochastic ranking for constrained evolutionary optimization, IEEE Trans. Evol. Comput. 4, 2000, pp. 284–294

[31] 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.

[32] 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.