ISSN : 2348-9065 (Online)
ISSN : XXXX - XXXX (Print)

Improved Cuckoo Search Algorithm for Solving Optimal Reactive Power Dispatch Problem

[I]K. Lenin, [II]Dr. B.Ravindranath Reddy, [III]Dr. M.Surya Kalavathi
[I]Research Scholar, Dept of EEE Jawaharlal Nehru Technological University, Kukatpally, Hyderabad, India
[II]Deputy Executive Engineer, Jawaharlal Nehru Technological University Kukatpally, Hyderabad, India
[III]Professor of Electrical and Electronics Engineering, Jawaharlal Nehru Technological University, Kukatpally, Hyderabad, India

Abstract
This paper presents an improved cuckoo search algorithm to solve the multi-objective reactive power dispatch problem. Modal analysis of the system is used for static voltage stability assessment. Loss minimization and maximization of voltage stability margin are taken as the objectives. Generator terminal voltages, reactive power generation of the capacitor banks and tap changing transformer setting are taken as the optimization variables. The cuckoo search (CS) algorithm is a recently developed meta-heuristic optimization algorithm, which is suitable for solving optimization problems. To enhance the accuracy and convergence rate of this algorithm, an improved cuckoo search algorithm is proposed in this paper to solve reactive power optimization problem. Normally, the parameters of the cuckoo search are kept constant. This may lead to decreasing the efficiency of the algorithm. To cope with this issue, a proper strategy for tuning the cuckoo search parameters has been presented. In order to evaluate the performance of the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other algorithms. Simulation results show's that (ICS) is more efficient than others in solving the optimal reactive power dispatch (ORPD) problem.

Key words
Modal analysis, optimal reactive power, Transmission loss, Cuckoo search algorithm, global optimization, Lévy flight, meta-heuristic, tuning

I. Introduction

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. It involves a non linear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1-2], Newton method [3] and linear programming [4-7].The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input- output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8, 9].

Because of computational drawbacks of conventional numerical methods in solving complex optimization problems, researchers may have to rely on meta-heuristic algorithms. Over the last decades, many meta-heuristic algorithms have been successfully applied to various engineering optimization problems (Sim 2003; Qing 2006; Zhang 2006; Sickel 2007; Sanchis 2008; Marinakis 2008; Serrurier 2008). For most complicated real-world optimization problems, they have provided better solutions in comparison with conventional numerical methods. To imitate natural phenomena, most meta-heuristic algorithms combine rules and randomness. These phenomena include the biological evolutionary processes, such as genetic algorithm (GA) (Holland 1975; Goldberg 1989), evolutionary algorithm (Fogel 1996; De Jong 1975) and differential evolution (DE) (Storn 1996), animal behavior, such as particle swarm optimization (PSO) (Kennedy 1995), tabu search (Glover 1977) and ant colony algorithm (ACA) (Dorigo 1996), as well as physical annealing processes, such as simulated annealing (SA)(Kirkpatrick 1983) , imitating animal behavior. The optimal solutions obtained by the CS [27] are far better than the best solutions obtained by efficient particle swarm optimizers and genetic algorithms (Yang 2010).

Cuckoos [26] are fascinating birds, not only because of the beautiful sounds they can make, but also because of their aggressive reproduction strategy. Some species such as the ani and Guira cuckoos lay their eggs in communal nests, though they may remove others' eggs to increase the hatching probability of their own eggs. Quite a number of species engage the obligate brood parasitism by laying their eggs in the nests of other host birds (often other species). There are three basic types of brood parasitism: intraspecific brood parasitism, cooperative breeding, and nest takeover. Some host birds can engage direct conflict with the intruding cuckoos. If a host bird discovers the eggs are not their owns, they will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere.

Some cuckoo species such as the New World brood-parasitic Tapera have evolved in such a way that female parasitic cuckoos are often very specialized in the mimicry in colour and pattern of the eggs of a few chosen host species. This reduces the probability of their eggs being abandoned and thus increases their reproductivity. In addition, the timing of egg-laying of some species is also amazing. Parasitic cuckoos often choose a nest where the host bird just laid its own eggs. The performance of the proposed algorithm (ICS) has been evaluated in standard IEEE 30 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

II. Voltage Stability Evaluation

A. Modal analysis for voltage stability evaluation

Modal analysis is one of the methods for voltage stability enhancement in power systems. In this method, voltage stability analysis is done by computing eigen values and right and left eigen vectors of a jacobian matrix. It identifies the critical areas of voltage stability and provides information about the best actions to be taken for the improvement of system stability enhancements. The linearized steady state system power flow equations are given by.

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} = \begin{bmatrix} J_{p\theta} & J_{pv} \\ J_{q\theta} & J_{QV}\end{bmatrix} \quad (1)$$

Where

ΔP = Incremental change in bus real power.
ΔQ = Incremental change in bus reactive Power injection
$\Delta\theta$ = incremental change in bus voltage angle.
ΔV = Incremental change in bus voltage Magnitude
$J_{p\theta}$, J_{PV}, $J_{Q\theta}$, J_{QV} jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q. However at each operating point we keep P constant and evaluate voltage stability by considering incremental relationship between Q and V.

To reduce (1), let $\Delta P = 0$, then.

$$\Delta Q = [J_{QV} - J_{Q\theta} J_{P\theta}^{-1} J_{PV}]\Delta V = J_R \, \Delta V \quad (2)$$

$$\Delta V = J^{-1} - \Delta Q \quad (3)$$

Where

$$J_R = (J_{QV} - J_{Q\theta} J_{P\theta-1} JPV \quad (4)$$

J_R is called the reduced Jacobian matrix of the system.

B. Modes of Voltage instability:

Voltage Stability characteristics of the system can be identified by computing the eigen values and eigen vectors

Let

$$J_R = \xi\wedge\eta \quad (5)$$

Where,

ξ = right eigenvector matrix of JR
η = left eigenvector matrix of JR
$\wedge$ = diagonal eigenvalue matrix of JR and

$$J^{R-1} = \xi\wedge^{-1}\eta \quad (6)$$

From (3) and (6), we have

$$\Delta V = \xi\wedge{-1}\,\eta\Delta Q \quad (7)$$

or

$$\Delta V = \sum_I \frac{\xi_i \eta_i}{\lambda_i} \Delta Q \quad (8)$$

Where ξ_i is the ith column right eigenvector and η the ith row left eigenvector of J_R.

λ_i is the ith eigen value of J_R.

The ith modal reactive power variation is,

$$\Delta Q_{mi} = K_i \xi_i \quad (9)$$

where,

$$K_i = \Sigma_j \xi_{ij}^{2-1} \quad (10)$$

Where

ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

$$\Delta V_{mi} = [1/\lambda_i]\Delta Q_{mi} \quad (11)$$

It is seen that, when the reactive power variation is along the direction of ξ_i the corresponding voltage variation is also along the same direction and magnitude is amplified by a factor which is equal to the magnitude of the inverse of the ith eigenvalue. In this sense, the magnitude of each eigenvalue λ_i determines the weakness of the corresponding modal voltage. The smaller the magnitude of λ_i, the weaker will be the corresponding modal voltage. If $|\lambda_i| = 0$ the ith modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

In (8), let $\Delta Q = e_k$ where e_k has all its elements zero except the kth one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} \quad (12)$$

η_{1k} k th element of η_1
V –Q sensitivity at bus k
V –Q sensitivity at bus k

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \quad (13)$$

III. Problem Formulation

The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss and maximize the static voltage stability margins (SVSM). This objective is achieved by proper adjustment of reactive power variables like generator voltage magnitude (gi) V , reactive power generation of capacitor bank (Qci), and transformer tap setting (tk).Power flow equations are the equality constraints of the problems, while the inequality constraints include the limits on real and reactive power generation, bus voltage magnitudes, transformer tap positions and line flows

A. Minimization of Real Power Loss

It is aimed in this objective that minimizing of the real power loss (Ploss) in transmission lines of a power system. This is mathematically stated as follows.

$$P_{loss=} \sum_{\substack{k=1\\ k=(i,j)}}^{n} g_{k(V_i^2+V_j^2-2V_i\,V_j\,\cos\theta_{ij})} \quad (14)$$

Where n is the number of transmission lines, gk is the conductance of branch k, V_i and V_j are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

B. Minimization of Voltage Deviation

It is aimed in this objective that minimizing of the Deviations in voltage magnitudes (VD) at load buses. This is mathematically stated as follows.

$$\text{Minimize VD} = \sum_{k=1}^{nl} |V_k - 1.0| \quad (15)$$

Where nl is the number of load busses and V^k is the voltage magnitude at bus k.

C. System Constraints

In the minimization process of objective functions, some problem constraints which one is equality and others are inequality had to be met. Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

ISSN : 2348-9065 (Online)
ISSN : XXXX - XXXX (Print)

$$P_{Gi} - P_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = C \quad 1.2 \ldots\ldots nb \qquad (16)$$

$$Q_{Gi} - Q_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots, nb \qquad (17)$$

where, nb is the number of buses, P_G and Q_G are the real and reactive power of the generator, PD and Q_D are the real and reactive load of the generator, and Gij and Bij are the mutual conductance and susceptance between bus i and bus j.Generator bus voltage (V_{Gi}) inequality constraint:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng \qquad (18)$$

Load bus voltage (VLi) inequality constraint:

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl \qquad (19)$$

Switchable reactive power compensations (QCi) inequality constraint:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc \qquad (20)$$

Reactive power generation (QGi) inequality constraint:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng \qquad (21)$$

Transformers tap setting (Ti) inequality constraint:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \qquad (22)$$

Transmission line flow (S_{Li}) inequality constraint:

$$S_{Li} \leq S_{Li}^{max}, i \in nl \qquad (23)$$

The load flow equality constraints are satisfied by
Power flow algorithm. The generator bus voltage (V_{Gi}), the transformer tap setting (T_i) and the Switchable reactive power Compensations (Q_{Ci}) are optimization variables and they are self-restricted between the minimum and maximum value by the ICS algorithm The limits on active power generation at the slack bus(PGs), load bus voltages (V_{Li}) and reactive power generation (Q_{Gi}), transmission line flow (S_{Li}) are state variables. They are restricted by adding a penalty function to the objective functions.

IV. Cuckoo Search Algorithm

The CS was inspired 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 imitate the colours and patterns of the eggs of a few chosen host species. This reduces the probability of the eggs being abandoned and, therefore, increases their re-productivity (Payne 2005). In general, the cuckoo eggs hatch slightly earlier than their host eggs. Once the first cuckoo chick is hatched, his first instinct action is to evict the host eggs by blindly propelling the eggs out of the nest. This action results in increasing the cuckoo chick's share of food provided by its host bird (Payne 2005). Moreover, studies show that a cuckoo chick can imitate the call of host chicks to gain access to more feeding opportunity. The CS models such breeding behavior and, thus, can be applied to various optimization problems. Yang and Deb (Yang 2009; Yang 2010), discovered that the performance of the CS can be improved by using Lévy Flights instead of simple random walk.

A. Lévy Flights

In nature, animals search for food in a random or quasi random manner. Generally, the foraging path of an animal is effectively a random walk because the next move is based on both the current location/state and the transition probability to the next location. The chosen direction implicitly 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 (Brown 2007). A Lévy flight is a random walk in which the step-lengths are distributed according to a heavy-tailed probability distribution. After a large number of steps, the distance from the origin of the random walk tends to a stable distribution.

B. Cuckoo Search Implementation

Each egg in a nest represents a solution, and a cuckoo egg represents a new solution. The aim is to employ the new and potentially better solutions (cuckoos) to replace not-so-good solutions in the nests. In the simplest form, each nest has one egg. The algorithm can be extended to more complicated cases in which each nest has multiple eggs representing a set of solutions (Yang 2009; Yang 2010). The CS is based on three idealized rules:

- Each cuckoo lays one egg at a time, and dumps it in a randomly chosen nest;
- The best nests with high quality of eggs (solutions) will carry over to the next generations;
- The number of available host nests is fixed, and a host can discover an alien egg with probability pa ϵ In this case, the host bird can either throw the egg away or abandon the nest to build a completely new nest in a new location (Yang 2009).

For simplicity, the last assumption can be approximated by a fraction pa of the n nests being replaced by new nests, having new random solutions. For a maximization problem, the quality or fitness of a solution can simply be proportional to the objective function. Other forms of fitness can be defined in a similar way to the fitness function in genetic algorithms (Yang 2009).
Based on the above-mentioned rules, the basic steps of the CS can be summarized as the pseudo code, as follows (Yang 2009):

Begin
Objective function f(x), $x = (x_1, \ldots\ldots, x_d)^T$
Generate initial population of
n host nests xi , (i = 1,2,..,n)
While(t Max Generation) or (stop criterion)
Get a cuckoo randomly by Lévy flights
Evaluate its quality / fitness F_i
Choose a nest among n (say.j) randomly
If ($F_i > F_j$)
replace j by the new solution;
endif
A fraction (p_a) of worse nests
are 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 xi (t+1) for the ith cuckoo, the following Lévy flight is performed

$$x_i(t+1) = x_i(t) + \alpha \,\Theta\, \text{Levy}(\lambda) \qquad (24)$$

where α is the step size, which should be related to the scale of the problem of interest. The product Θ means entry-wise multiplications (Yang 2010). In this research work, we consider a Lévy flight in which the step-lengths are distributed according to the following probability distribution

Levyu=,t^{λ},1<λ ≤3 (25)

which has an infinite variance. Here, the consecutive jumps/steps of a cuckoo essentially form a random walk process which obeys a power-law step-length distribution with a heavy tail. It is worth pointing out that, in the real world, if a cuckoo's egg is very similar to a host's eggs, then this cuckoo's egg is less likely to be discovered, thus the fitness should be related to the difference in solutions. Therefore, it is a good idea to do a random walk in a biased way with some random step sizes (Yang 2009).

V. Improved Cuckoo Search

The parameters pa , λ and α introduced in the CS help the algorithm to find globally and locally improved solutions, respectively. The parameters pa and α are very important parameters in fine-tuning of solution vectors, and can be potentially used in adjusting convergence rate of algorithm. The traditional CS algorithm uses fixed value for both pa and α. These values are set in the initialization step and cannot be changed during new generations. The main drawback of this method appears in the number of iterations to find an optimal solution. If the value of pa is small and the value of α is large, the performance of the algorithm will be poor and leads to considerable increase in number of iterations. If the value of pa is large and the value of α is small, the speed of convergence is high but it may be unable to find the best solutions.

The key difference between the ICS and CS is in the way of adjusting pa and α. To improve the performance of the CS algorithm and eliminate the drawbacks lies with fixed values of pa and α , the ICS algorithm uses variables pa and α. In the early generations, the values of pa and α must be big enough to enforce the algorithm to increase the diversity of solution vectors. However, these values should be decreased in final generations to result in a better fine-tuning of solution vectors. The values of pa and α are dynamically changed with the number of generation and expressed in Equations (26- 28), where NI and gn are the number of total iterations and the current iteration, respectively.

$$p_a(gn)=p_{a\,max} - \frac{gn}{NI}\,(p_{a\,max} - p_{a\,min}) \quad (26)$$

$$\alpha\,(gn) = \alpha_{max}\ \exp\,(c.\,gn) \quad (27)$$

$$\alpha\,(gn) = \alpha_{max}\ \exp\,(c.\,gn) \quad (28)$$

VI. Simulation Results

The validity of the proposed Algorithm has been demonstrated on IEEE-30 bus system. The IEEE-30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are with the tap setting transformers. The real power settings are taken from [1]. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses and 1.05 p.u. for all the PQ buses and the reference bus.

Table 1: Voltage Stability under Contingency State

Sl.No	Contigency	ORPD Setting	Vscrpd Setting
1	28-27	0.1400	0.1422
2	4-12	0.1658	0.1662
3	1-3	0.1784	0.1754
4	2-4	0.2012	0.2032

Table 2 : Limit Violation Checking Of State Variables

State variables	limits		ORPD	VSCRPD
	Lower	upper		
Q1	-20	152	1.3422	-1.3269
Q2	-20	61	8.9900	9.8232
Q5	-15	49.92	25.920	26.001
Q8	-10	63.52	38.8200	40.802
Q11	-15	42	2.9300	5.002
Q13	-15	48	8.1025	6.033
V3	0.95	1.05	1.0372	1.0392
V4	0.95	1.05	1.0307	1.0328
V6	0.95	1.05	1.0282	1.0298
V7	0.95	1.05	1.0101	1.0152
V9	0.95	1.05	1.0462	1.0412
V10	0.95	1.05	1.0482	1.0498
V12	0.95	1.05	1.0400	1.0466
V14	0.95	1.05	1.0474	1.0443
V15	0.95	1.05	1.0457	1.0413
V16	0.95	1.05	1.0426	1.0405
V17	0.95	1.05	1.0382	1.0396
V18	0.95	1.05	1.0392	1.0400
V19	0.95	1.05	1.0381	1.0394
V20	0.95	1.05	1.0112	1.0194
V21	0.95	1.05	1.0435	1.0243
V22	0.95	1.05	1.0448	1.0396
V23	0.95	1.05	1.0472	1.0372
V24	0.95	1.05	1.0484	1.0372
V25	0.95	1.05	1.0142	1.0192
V26	0.95	1.05	1.0494	1.0422
V27	0.95	1.05	1.0472	1.0452
V28	0.95	1.05	1.0243	1.0283
V29	0.95	1.05	1.0439	1.0419
V30	0.95	1.05	1.0418	1.0397

Table 3 : Comparison of Real Power Loss

Method	Minimum loss
Evolutionary programming [30]	5.0159
Genetic algorithm[31]	4.665
Real coded GA with Lindex as SVSM [32]	4.568
Real coded genetic algorithm [33]	4.5015
Proposed ICS	4.2998

VII. Conclusion

In this paper a novel approach ICS algorithm used to solve optimal reactive power dispatch problem. The performance of the proposed algorithm has been demonstrated by simulating it in

ISSN : 2348-9065 (Online)
ISSN : XXXX - XXXX (Print)

standard IEEE 30 bus test system.The simuation results reveals about performance of the proposed ICS algorithm and the real power loss has been considerably reduced, when compared to other standard algorithms [30-33] .

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

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

[10] Brown C, Liebovitch LS, Glendon R (2007) Lévy flights in Dobe Ju/hoansi foraging patterns, Hum Ecol. 35:129-138.

[11] De Jong K (1975) Analysis of the behavior of a class of genetic adaptivesystems, Ph.D. Dissertation, University of Michigan, Ann Arbor, MI.Dorigo M, Maniezzo V, Golomi A (1996) Ant system: optimization by a colony of cooperating agents. IEEE T Syst Man Cy B 26 (1) 29–41.

[12] Fogel LJ, Owens AJ, Walsh MJ (1966) Artificial intelligence through simulated evolution, John Wiley, Chichester, UK.

[13] Glover F (1977) Heuristic for integer programming using surrogate constraints, Decision Sci. 8 (1):156–166. Goldberg DE (1989) Genetic algorithms in search, optimization and machine learning, Addison Wesley, Boston, USA.

[14] Holland JH (1975) Adaptation in natural and artificial systems. University of Michigan Press, Ann Arbor, USA.

[15] Kennedy J, Eberhart RC (1995) Particle swarm optimization, In: Proceedings of IEEE International Conference on Neural Networks. 1942–1948.

[16] Kirkpatrick S, Gelatt C, Vecchi M (1983) Optimization by simulated annealing, Sciene. 220:671–680.

[17] Koza JR (1990) Genetic programming: a paradigm for genetically breeding populations of computer programs to solve problems,Stanford University, USA.

[18] Marinakis Y, Marinaki M, Dounias G (2008) Particle swarm optimization for pap- smear diagnosis. Expert Syst Appl 35 (4):1645–1656.

[19] Payne R B, Sorenson M D, Klitz K (2005) The cuckoos. Oxford University Press.

[20] Qing AY (2006) Dynamic differential evolution strategy and applications in electromagnetic inverse scattering problems. IEEE T Geosci Remote 44 (1):116–125.

[21] Sanchis J, Martanez MA, Blasco X (2008) Integrated multiobjective optimization and a priori preferences using genetic algorithms. Inform Sciences 178(4):931–951.

[22] Serrurier M, Prade H (2008) Improving inductive logic programming by using simulated annealing. Inform Sciences 178 (6):1423–1441.

[23] Sickel JHV, Lee KY, Heo JS (2007) Differential evolution and its applications to power plant control. In: International Conference on Intelligent Systems Applications to Power Systems, ISAP, 1–6.

[24] Sim KM, Sun WH (2003) Ant colony optimization for routing and loadbalancing: survey and new directions. IEEE T Syst Man Cy A 33 (5):560– 572.

[25] Storn R (1996) Differential evolution design of an IIR-filter. Paper presented in: IEEE International Conference on Evolutionary Computation, Nagoya, 268–273 1996.

[26] Yang XS, Deb S (2009) Cuckoo search via Lévy flights, In: Proceeings of World Congress on Nature & Biologically Inspired Computing (NaBIC 2009, India), 210-214.

[27] Yang XS, Deb S (2010) Engineering Optimisation by Cuckoo Search, Int. J. Mathematical Modelling and Numerical Optimisation, 1(4):330–343.

[28] Zhang JJ, Zhang YH, Gao RZ (2006) Genetic algorithms for optimal design of vehicle suspensions. Paper presented in IEEE International Conference on Engineering of Intelligent Systems,1–6.

[29] Zou DX, et al., (2010) Novel global harmony search algorithm for unconstrained problems, Neuro computing. 73:3308-3318.International Journal of Communications and Information Technology, IJCIT IJCIT-2011-Vol.1-No.1 Dec. 2011.

[30] Wu Q H, Ma J T. Power system optimal reactive power dispatch using evolutionary programming. IEEE Transactions on power systems 1995; 10(3): 1243-1248

[31] S.Durairaj, D.Devaraj, P.S.Kannan,' Genetic algorithm applications to optimal reactive power dispatch with voltage stability enhancement', IE(I) Journal-EL Vol 87,September 2006.

[32] D.Devaraj ,'Improved genetic algorithm for multi – objective reactive power dispatch problem' European Transactions on electrical power 2007 ; 17: 569-581

[33] P. Aruna Jeyanthy and Dr. D. Devaraj "Optimal Reactive Power Dispatch for Voltage Stability Enhancement Using Real Coded Genetic Algorithm" International Journal of Computer and Electrical Engineering, Vol. 2, No. 4, August, 2010 1793-8163