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Hybrid Algorithm's For Solving Optimal Reactive Power Dispatch Problem

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ABSTARCT

In this paper, a new search Hybrid algorithm (HA) is proposed to solve the optimal reactive power dispatch (ORPD) Problem. The ORPD problem is formulated as a nonlinear constrained single-objective optimization problem where the real power loss and the bus voltage deviations are to be minimized separately. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system consisting 6 generator and compared other algorithms reported those before in literature. Results show that HS is more efficient than others for solution of single-objective ORPD problem.

Key words: Particle swarm optimization, genetic algorithm, Swarm Intelligence, optimal reactive power, Transmission loss.

INTRODUCTION

In recent years the optimal reactive power dispatch (ORPD) problem has received great attention as a result of the improvement on economy and security of power system operation. Solutions of ORPD problem aim to minimize object functions such as fuel cost, power system loses, etc. while satisfying a number of constraints like limits of bus voltages, tap settings of transformers, reactive and active power of power resources and transmission lines and a number of controllable Variables [1, 2]. In the literature, many methods for solving the ORPD problem have been done up to now. At the beginning, several classical methods such as gradient based [3], interior point [4], linear programming [5] and quadratic programming [6] have been successfully used in order to solve the ORPD problem. However, these methods have some disadvantages in the Process of solving the complex ORPD problem. Drawbacks of these algorithms can be declared insecure convergence properties, long execution time, and algorithmic complexity. Besides, the solution can be trapped in local minima [1-10]. In recent years, many different optimization techniques have been proposed for solving the complex, multimodal functions in several fields [11-14]. Some of the well-known optimization algorithms are the Genetic Algorithm (GA), Particle Swarm Optimization (PSO) algorithm, Ant Colony Optimization (ACO) algorithm, Differential Evolution (DE) algorithm, and Harmony Search (HS) algorithm. These algorithms are used in various fields by many researchers to obtain the optimum value of the problems [15-20]. Each optimization algorithm uses different properties to keep a balance between the exploration and exploitation goals which can be a key for the success of an algorithm. Exploration attribute of an algorithm enables the algorithm to test several areas in the search space. On the other hand, exploitation attribute makes the algorithm focus the search around the possible candidates. Although the optimization algorithms have positive characteristics, it is shown that these algorithms do not always perform as well as it is desired [21]. Because of this, hybrid algorithms are growing area of interest since their solution quality can be made better than the algorithms that form them by combining their desirable features. Hybridization is simply the combination of two or more techniques in order to outperform their performances by the use of their good properties together. Hybridization has been done in several different ways in the literature and it is observed that the new hybridization techniques are very efficient and effective for optimization [21-26]. A novel hybrid algorithm proposed in this paper is called HA and it is a combination of three well known evolutionary algorithms, namely Differential Evolution (DE) algorithm, Particle Swarm Optimization (PSO) algorithm, and Harmony Search (HS) algorithm. It merges the general operators of each algorithm recursively. This achieves both good exploration and exploitation in HA without altering their individual properties. The performance of HA 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. The effectiveness of the proposed approach is demonstrated through IEEE-30 bus system. The test results show the proposed algorithm gives better results with less computational burden and is fairly consistent in reaching the near optimal solution.

MATERIA L AND METHODS

Voltage Stability Evaluation

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.

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{p\theta} & J_{pv} \\ J_{q\theta} & J_{QV} \end{bmatrix} \quad (3)$$

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.

$$\Delta Q = \left[J_{QV} - J_{Q\theta} J_{P\theta}{}^{-1} J_{PV}\right] \Delta V = J_R \Delta V \quad (4)$$

$\Delta V = J^{-1} - \Delta Q$ (5)

Where

$J_R = \left(J_{QV} - J_{Q\theta} J_{P\theta^{-1}} JPV\right)$ (6)

J_R is called the reduced Jacobian matrix of the system.

Modes of Voltage instability:

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

Let

$J_R = \xi \wedge \eta$ (7)

Where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of J_R

$\wedge$ = diagonal eigenvalue matrix of J_R and

$J_{R^{-1}} = \xi \wedge^{-1} \eta$ (8)

From (5) and (8), we have

$\Delta V = \xi \wedge^{-1} \eta \Delta Q$ (9)

or

$\Delta V = \sum_I \frac{\xi_i \eta_i}{\lambda_i} \Delta Q$ (10)

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,

$\Delta Q_{mi} = K_i \xi_i$ (11)

where,

$K_i = \sum_j \xi_{ij^2} - 1$ (12)

Where

ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

$\Delta V_{mi} = [1/\lambda_i] \Delta Q_{mi}$ (13)

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 Eigen value. In this sense, the magnitude of each Eigen value 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 (10), let $\Delta Q = e_k$ where e_k has all its elements zero except the kth one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} \quad (14)$$

η_{1k} k th element of η_1

V –Q sensitivity at bus k

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \quad (15)$$

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.

$$P_{loss} = \sum_{\substack{k=1\\k=(i,j)}}^{n} g_{k(V_i^2+V_j^2-2V_i V_j \cos\theta_{ij})} \quad (16)$$

Where n is the number of transmission lines, g_k 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.

$$\text{Minimize VD} = \sum_{k=1}^{nl} |V_k - 1.0| \quad (17)$$

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:

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

(18)

(19)

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

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, i \in ng \quad (20)$$

Load bus voltage (*VLi*) inequality constraint:

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl \quad (21)$$

Switchable reactive power compensations (*QCi*) inequality constraint:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc \quad (22)$$

Reactive power generation (*QGi*) inequality constraint:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng \quad (23)$$

Transformers tap setting (T_i) inequality constraint:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \quad (24)$$

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

$$S_{Li}^{min} \leq S_{Li}^{max}, i \in nl \quad (25)$$

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

HA ALGORITHM

In the literature, many different ways of combining the well-known algorithms are performed to obtain more powerful optimization algorithms [21-26]. The main aim of the hybridization is to use different properties of different algorithms to improve the solution quality.

Among the well-known algorithms, DE, PSO and HS algorithms are the three algorithms that are used in many fields by researchers and these algorithms are proven to be very powerful optimization tools [5-8]. Each algorithm has different strong features. As an example, DE usually requires less computational time and also has better approximation of solutions for most of the problems. PSO generally avoids the solution from trapping into local minima by using its diversity. HS on the other hand, is an efficient algorithm that has a very good performance on different applications.

HA uses the operators of these three algorithms with randomly selected parameters consecutively and by not altering their properties. The new candidate set, obtained by each algorithm, is used as a new solution set for the other algorithm.

HA algorithm for solving reactive power dispatch problem.

Step 1. Generation of the candidate population with given dimensions: Initialize the candidate population X_{ij} in a given range.

Step 2. *Crossover and mutation operators of DE:* The mutation and crossover operators are applied to find the better approximation to a solution by using (26), (27), and (28)

The mutant vector V_{ij} is calculated as corresponding to each member in population using (1) where *a, b,* and *c* are distinct numbers. Mutant vector V_{ij} is crossoverred with X_{ij} and trial vector U_{ij} is generated by using (27) where rj is a uniformly distributed number for each jth parameter of X_i. Also, *F* and *CR* are the main control parameters of DE.

$$V_i = X_a + F(X_b - X_c) \quad (26)$$

$$U_{ij} = \begin{cases} V_{ij} \; if \; r_j \leq CR \\ X_{ij} \; otherwise \end{cases} \quad (27)$$

$$X_i = \begin{cases} U_i \; if \; f(U_i) < f(X_i) \\ X_i \; otherwise \end{cases} \quad (28)$$

Selection process determines U_{ij} to survive to the next generation by using (28).

Step 3. *Particle movement by PSO:* The randomly selected parameters are applied on the velocities by using (29). When a better solution is being discovered, all particles improve their positions by using (30). This movement avoids the particles to be trapped to the local minima by increasing the diversity of solution. V_{ij} refers to the velocity values and for each row is calculated according to the control parameters c_1, c_2, and w by using (29). $global_{best}$ is the best position obtained by any particle and P_{best} is the personal best of a particle. X_{ij} refers to current positions of a particle and can be updated by using (30) for each row.

$$V_i = w * V_i + c_1 * (P_{best} - X_i) + c_2 * (global_{best} - X_i) \tag{29}$$

$$X_i = X_i + V_i \tag{30}$$

Step 4. *Choosing a neighbouring value by HS:* HS cansearch in different zones of the search space by using the control parameters that are *hmcr*, *par* and *fw*. With a given probability of *hmcr*, a value is selected from the candidate population. With a given probability of 1-*hmcr*, a random candidate is generated in the given range. The population can have non-updated candidates to keep the diversity in the population with a given probability of 1-*par*. With a given probability of *par*, the candidates are updated by applying (31) where rand() is a random number ∈(-1,1).

$$X_i = X_i + rand() * fw \tag{31}$$

Step 5. Consecutively Step 2, Step 3, and Step 4 are applied. The algorithm is performed until the termination criterion is not satisfied. Elitism is included in HDPH by keeping the best solution at the end of each iteration.

RESULTS AND DISCUSSION

The validity of the proposed Algorithm technique is 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[27]	5.0159
Genetic algorithm[28]	4.665
Real coded GA with Lindex as SVSM[29]	4.568
Real coded genetic algorithm[30]	4.5015
Proposed HA method	4.1074

CONCLUSION

In this paper, one of the recently developed stochastic algorithms HA has been demonstrated and applied to solve optimal reactive power dispatch problem. The problem has been formulated as a constrained optimization problem. Different objective functions have been considered to minimize real power loss, to enhance the voltage profile. The proposed approach is applied to optimal reactive power dispatch problem on the IEEE 30-bus power system. The simulation results indicate the effectiveness and robustness of the proposed algorithm to solve optimal reactive power dispatch problem in test system. The HS approach can reveal higher quality solution for the different objective functions in this paper.

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] 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** .
[11] Z.W. Geem, J.H. Kim, and G.V. Loganathan, "A New Heuristic Optimization Algorithm: Harmony Search", Simul., Trans. of the Soc. for Model. and Simul. Int., pp. 60-68, **2001**.
[12] J. Kennedy, R. Eberhart, "Particle Swarm Optimization. Piscataway", Proc. of IEEE Int. Conf. on Neural Netw. IV, NJ: IEEE Press, pp. 1942-1948, **1995**.
[13] R. Storn, K. Price, "Differential Evolution; A Simple an Efficient Heuristic for Global Optimization over Continuous Spaces", J. of Glob. Optim., vol.11, pp. 341-359, **1997**.
[14] M. Dorigo, G. Dicaro, "Ant colony optimization: A new metaheuristic", Evol. Comput. CEC 99. Proc. of the 1999 Congr. on., vol. 2, pp. 1470-1477, **1999**.
[15] F. Wenlong, M. Johnston, and M.Zhang, "Soft edge maps from edge detectors evolved by genetic programming", Evol. Comput. Proc. IEEE, pp.1-8, **2012**.
[16] R. Storn, "Differential Evolution Design of an IIR-filter", Evol. Comput. Proc. IEEE, pp. 268-273, **1996**.
[17] Z.W. Geem, J.H. Kim, and G.V. Loganathan, "Harmony Search optimization, Application to pipe network design", Int. J. of Model.&Simul., vol. 22, pp. 125-133, **2002**.
[18] Z.W. Geem, C. Tseng, and Y. Park, "Harmony Search for Generalized Orienteering Problem: Best touring in China", Springer Lect. Notes in Comput. Sci., vol. 3412, pp. 741-750, **2005**.

[19] I. Hitoshi, “Using genetic programming to predict financial data”, Evol. Comput. CEC 99. Proc. of the 1999 Congr. on., vol.1, pp.244-251, **1999**.
[20] R.S. Parpinelli, H.S. Lopes, and A.A. Freitas, “Data mining with an Ant Colony Optimization Algorithm”, IEEE Trans. on Evol. Comput., vol.6, pp. 312-332, **2002**.
[21] R. Thangaraj, M. Pant, A. Abraham, and P. Bouvry, “Particle Swarm Optimization: Hybridization perspectives and experimental illustrations”, Appl. Math. and Comput., vol. 217, pp. 5208-5226, **2011**.
[22] X.H. Shi, Y.C. Liang, and L.M. Wang, “An improved GA and novel PSO-GA-based hybrid algorithm”, Inf. Process. Lett., vol. 93, pp. 255-261, **2005**.
[23] N. Holden, A.A. Freitas, “A hybrid particle swarm/ant colony algorithm for the classification of hierarchical biological data.”Swarm Intell. Symp. SIS 2005, pp.100-107, **2005**.
[24] A.A.A. Esmin, G.T. Torres, and G.B. Alvarenga, “Hybrid Evolutionary Algorithm Based on PSO and GA mutation”, In proc. of the Sixth Int. Conf. on Hybrid Intell. Syst., pp.57, **2006**.
[25] H. Li, and H. Li, “A Novel Hybrid Particle Swarm Optimization Algorithm Combined with Harmony Search for High Dimensional Optimization Problems”, The Int. Conf. on Intell. Pervasive Comput., pp. 94-97, **2007**.
[26] I. Cionei, E. Kyriakides, “Hybrid Ant Colony-Genetic Algorithm (GAAPI) for Global Continuous Optimization”, IEEE Trans. On Syst., Man, and Cybern. - Part B
[27] 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 .
[28] 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**.
[29] D.Devaraj ,’ Improved genetic algorithm for multi – objective reactive power dispatch problem’ European Transactions on electrical power **2007** ; 17: 569-581.
[30] 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.