Hybrid Genetic Algorithm and Particle Swarm Optimization (HGAPSO) Algorithm for Solving Optimal Reactive Power Dispatch Problem

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***Abstract*—This paper presents an algorithm for solving the multi-objective reactive power dispatch problem in a power system. 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. This paper introduces, an evolutionary algorithm based on the hybrid genetic algorithm (GA) and particle swarm optimization (PSO), denoted by HGAPSO is used to solve reactive power dispatch problem.**

***Index Terms*—modal analysis, optimal reactive power, transmission loss, genetic algorithm, particle swarm optimization, optimization**

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]. In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point [10]. The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Voltage stability evaluation using modal analysis [10] is used as the indicator of voltage stability. The optimization of systems and processes is very important to the efficiency and economics of many science and engineering domains. Optimization problems are solved by using rigorous or approximate mathematical search techniques. Rigorous approaches have employed linear programming, integer programming, dynamic programming or branch-and-bound techniques to arrive at the optimum solution for moderate-size problems. However, optimizing real-life problems of the scale often encountered in engineering practice is much more challenging because of the huge and complex solution space. Finding exact solutions to these problems turn out to be NP-hard. Researchers have developed computational systems that mimic the efficient behavior of species such as ants, bees, birds and frogs, as a means to seek faster and more robust solutions to complex optimization problems. The first evolutionary based technique introduced in the literature was the genetic algorithm (Holland 1975) [11]. The computational drawbacks of existing numerical methods have forced researchers to rely on heuristic algorithms. Heuristic methods are powerful in obtaining the solution of optimization problems. Although these methods are approximate methods (i.e. their solutions are good, but probably not optimal), they do not require the derivatives of the objective function and constraints. Also, the heuristics use probabilistic transition rules instead of deterministic rules.

Here, an evolutionary algorithm based on the hybrid genetic algorithm (GA) and particle swarm optimization (PSO), denoted by HGAPSO, is developed in order to solve the optimal reactive power dispatch problem .The

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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

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

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

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 J_R

η = left eigenvector matrix of J_R

$\wedge$ = diagonal eigenvalue matrix of J_R 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 ξi is the ith column right eigenvector and η the i^{th} row left eigenvector of J_R.

λ_i is the ith eigen value of JR.

The i^{th} modal reactive power variation is,

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

where,

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

where

ξji is the jth element of ξi
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 ξi 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 λi determines the weakness of the corresponding modal voltage. The smaller the magnitude of λi, 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 k^{th} 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

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

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, Vi and Vj 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 Vk 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:

$$P_{Gi} - P_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb \quad (16)$$

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

where, *nb* is the number of buses, *PG* and *QG* are the real and reactive power of the generator, *PD* and *QD* 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 (*VGi*) inequality constraint:

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

Load bus voltage (*VLi*) inequality constraint:

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

Switchable reactive power compensations (QCi) inequality constraint:

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

Reactive power generation (*QGi*) inequality constraint:

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

Transformers tap setting (*Ti*) inequality constraint:

$$T_i^{min} \le T_i \le T_i^{max}, i \in nt \quad (22)$$

Transmission line flow (SLi) inequality constraint:

$$S_{Li}^{min} \le S_{Li}^{max}, i \in nl \quad (23)$$

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

IV. Genetic Algorithms and Particle Swarm Optimization

A. Basic Concepts of Genetic Algorithms

Genetic algorithm (GA) is a well-known and frequently used evolutionary computation technique. This method was originally developed by John Holland [11] and his PhD students Hassan *et al*. [12]. The idea was inspired from Darwin's natural selection theorem which is based on the idea of the survival of the fittest. The GA is inspired by the principles of genetics and evolution, and mimics the reproduction behavior observed in biological populations.

In GA, a candidate solution for a specific problem is called an individual or a chromosome and consists of a linear list of genes. GA begins its search from a randomly generated population of designs that evolve over successive generations (iterations), eliminating the need for a user-supplied starting point. To perform its optimization-like process, the GA employs three operators to propagate its population from one generation to another. The first operator is the "selection" operator in which the GA considers the principal of "survival of the fittest" to select and generate individuals (design solutions) that are adapted to their environment. The second operator is the "crossover" operator, which mimics mating in biological populations. The crossover operator propagates features of good surviving designs from the current population into the future population, which will have a better fitness value on average. The last operator is "mutation", which promotes diversity in population characteristics. The mutation operator allows for global search of the design space and prevents the algorithm from getting trapped in local minima [12].

B. Basic Concepts of PSO

Particle Swarm Optimization (PSO) is one of the recent evolutionary optimization methods. This technique was originally developed by Kennedy & Eberhart [13] in order to solve problems with continuous search space. PSO is based on the metaphor of social interaction and communication, such as bird flocking and fish schooling. This algorithm can be easily implemented and it is computationally inexpensive, since its memory and CPU speed requirements are low [14]. PSO shares many common points with GA. It conducts the search using a population of particles which correspond to individuals in GA. Both algorithms start with a randomly generated population. PSO does not have a direct recombination operator. However, the stochastic acceleration of a particle towards its previous best position, as well as towards the best particle of the swarm (or towards the best in its neighbourhood in the local version), resembles the recombination procedure in evolutionary computation [15]-[17].

Compared to GA, the PSO has some attractive characteristics. It has memory, so knowledge of good solutions is retained by all particles, whereas in GA, previous knowledge of the problem is destroyed once the population changes. PSO does not use the filtering operation (such as selection in GAs), and all the members of the population are maintained through the search procedure to share their information effectively.

The PSO was inspired from social behaviour of bird flocking. It uses a number of particles (candidate solutions) which fly around in the search space to find best solution. Meanwhile, they all look at the best particle (best solution) in their paths. In other words, particles consider their own best solutions as well as the best solution has found so far. Each particle in PSO should consider the current position, the current velocity, the distance to *pbest*, and the distance to *gbest* to modify its position. PSO was mathematically modelled as follow:

$$v_i^{t+1} = wv_i^t + c_1 \times rand \times (pbest_i - x_i^t) + c_2 \times rand \times (gbest - x_i^t) \quad (24)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (25)$$

The PSO starts with randomly placing the particles in a problem space. In each iteration, the velocities of particles are calculated using (24). After defining the velocities, the position of masses can be calculated as (25). The process of changing particles' position will continue until meeting an end criterion.

V. Hybrid of GA and PSO (HGAPSO)

Although GAs have been successfully applied to a wide spectrum of problems, using GAs for large-scale optimization could be very expensive due to its requirement of a large number of function evaluations for convergence. This would result in a prohibitive cost for computation of function evaluations even with the best computational facilities available today. Considering the efficiency of the PSO, and the compensatory property of GA and PSO, combining the searching abilities of both methods in one algorithm seems to be a logical approach. In this paper, the hybrid of GA and PSO named HGAPSO, originally presented by Juang [18], is used. This algorithm consists of four major operators: enhancement, selection, crossover, and mutation.

It is obvious that the feasible region in constrained optimization problems may be of any shape (convex or concave and connected or disjointed). In real-parameter constrained optimization using GAs, schemata specifying contiguous regions in the search space (such as 110*…*) may be considered to be more important than schemata specifying discrete regions in the search space (such as (*1*10*...*), in general. Since, any arbitrary contiguous region in the search space cannot be represented by single Holland's schema and since the feasible search space can usually be of any arbitrary shape, it is expected that the single-point crossover operator used in binary GAs will not always be able to create feasible children solutions from two feasible parent solutions. The floating-point representation of variables in a GA and a search operator that respects contiguous regions in the search space may be able to eliminate the above two difficulties associated with binary coding and single-point crossover. Hence, a floating point coding scheme is adopted here for all of the GA, PSO and HGAPSO. For the frame structures where design variables must have discrete values, the solutions are achieved by rounding the design variables to the nearest permissible integer number. An elitist strategy has been used in the algorithms of this work, where the best solution is given the opportunity to be directly carried over to the next generation.

A. Enhancement

In each generation, after the fitness values of all the individuals in the population are calculated, the top-half best performing ones are marked. These individuals are regarded as elites. Instead of reproducing the elites directly to the next generation as elite GAs do, we first enhance the elites. The enhancement operation tries to mimic the maturing phenomenon in nature, where individuals will become more suitable to the environment after acquiring knowledge from the society. Furthermore, by using these enhanced elites as parents, the generated offspring will achieve better performance than those bred by original elites [18]. The enhancement of the elites is performed by the velocity and position update procedures in PSO (Eqs. (24) and (25)). By analyzing the PSO, Perez and Behdinan [19] presented the stability conditions for the algorithm as shown below:

$$C_1 r_1 + C_2 r_2 > 0 \quad (26)$$

$$\frac{C_1 r_1 + C_2 r_2}{2} - \omega < 1 \quad (27)$$

$$\omega < 1 \quad (28)$$

Knowing that $r_1, r_2 \in [0,1]$, the following parameter selection heuristic was derived:

$$0 < C_1 + C_2 < 4 \quad (29)$$

$$\frac{c_1 + c_2}{2} - 1 < \omega < 1 \quad (30)$$

It was concluded that if C_1, C_2 and ω are selected with the heuristics specified in (24) and (25), the system will guaranteed convergence to an equilibrium point. In this article the parameters C_1, C_2 and ω are chosen considering the above conditions and according to the searching ability needed to solve each of the problems. Due to the importance of the inertia weight in controlling the global/local search behaviour of the PSO, a dynamic improvement has proven useful by forcing an initial global search with a high inertia weight ($\omega \approx 1$), and subsequently narrowing down the algorithm exploration to feasible areas of the design space by decreasing its value towards local search values ($\omega < 0.5$). In this approach, a dynamic decrease of ω value has been suggested based on a fraction multiplier (K_W) as shown in Eq. (31). When no improvements had been made for a predefined number of consecutive design iterations [20]:

$$\omega^{t+1} = K_W \omega^t \quad (31)$$

It should be noted that the elites in each generation can be from both groups of the previous generation, i.e., the enhanced elites or the produced offspring. If the elite *i* is an offspring produced by the parents of the previous generation, then v_i^t is set to zero, and p_i^t is set to x_i^t , i.e., the newly generated individual itself. Otherwise, p_i^t records the best solution of individual *i* evolved so far.

B. Selection

In the HGAPSO, the GA operations are performed on the enhanced elites achieved by PSO. In order to select parents for the crossover operation, the tournament selection scheme is used. Two enhanced elites are selected randomly, and their fitness values are compared to select the one with better fitness as a parent and place it in the mating pool. This scheme is used as the selection operator in the GA as well.

Crossover: Parents are selected randomly from the mating pool in groups of two and two offspring are created by performing crossover on the parent solutions. In this paper, a simulated binary crossover (SBX) is used. SBX operator is particularly suitable here because the spread of children solutions around parent solutions can be controlled using a distribution index, η_c . With this operator any arbitrary contiguous region can be searched, provided there is enough diversity maintained among the feasible parent solutions. Here, we have used small values for η_c at the first generations in order to have offspring solutions away from parents and to provide a global search. The value of η_c is increased with the increase of generation, guiding the algorithm towards a local search.

Mutation: The final genetic operator is mutation. It can create a new genetic material in the population to maintain the population's diversity. In this article, mutation is not applied to all of the population, and a mutation probability (P_m) is assigned to every individual according to its fitness value:

$$P_{mi} = 0.5\,x \left[\frac{F_{max}-F_i}{F_{max}-F_{ave}}\right] \quad \text{if } if\ F_i \geq F_{ave} \tag{32}$$

$$P_{mi} = \left[\frac{F_{ave}-F_i}{F_{max}-F_{ave}}\right] \qquad if\ F_i < F_{ave} \tag{33}$$

F_i is the fitness value of the individual *i*, F_{max} and F_{ave} are the maximum and average fitness values of the population in each generation. After assigning the P_m s, a random number in the range [0, 1] is created for each generation. The individuals having a P_m greater than this number is mutated.

The mutation operator used here is a variable dependent random mutation. In the random mutation operator, a solution is created in the vicinity of the parent solution with a uniform probability distribution [21]:

$$x_i^{(1,t+1)} = x_i^{(1,t)} + (r_i - 0.5)\Delta_i \tag{34}$$

r_i is a random number in [0, 1]. Δ_i is the user defined maximum perturbation allowed in the *i*th decision variable(x_i).Care should be taken to check if the above calculation takes $x_i^{(1,t+1)}$ outside of the specified lower and upper limits. In this approach, at each generation, Δ_i for a variable x_i is calculated using the average of that variable or the difference between its maximum and minimum in the population, i.e.

$$\Delta_i = 0.5\,x\,(\max(x_i) - \min(x_i)) \tag{35}$$

$$\Delta_i = (0.025 \sim 0.075)\,x\,ave\,(x_i) \tag{36}$$

After applying the GA operators, the offspring and the enhanced elites from PSO, form the new population and their fitness is evaluated and compared in order to select the elites for the next generation.

VI. Simulation Results

TABLE I. 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 II. 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

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 I&II shows about the voltage stability under contingency state, Limit violation also checked for sate variables. Finally real power loss has been compared with other algorithms, as shown in Table III. And results reveal that proposed method has been efficient in decreasing the real power loss.

TABLE III. COMPARISON OF REAL POWER LOSS

Method	Minimum loss
Evolutionary programming[22]	5.0159
Genetic algorithm[23]	4.665
Real coded GA with Lindex as SVSM[24]	4.568
Real coded genetic algorithm[25]	4.5015
Proposed HGAPSO method	4.3786

VII. CONCLUSION

In this paper a novel approach HGAPSO algorithm used to solve optimal reactive power dispatch problem, considering various generator constraints, has been successfully applied. The proposed method formulates reactive power dispatch problem as a mixed integer non-linear optimization problem and determines control strategy with continuous and discrete control variables such as generator bus voltage, reactive power generation of capacitor banks and on load tap changing transformer tap position. To handle the mixed variables a flexible representation scheme was proposed. The performance of the proposed algorithm demonstrated through its voltage stability assessment by modal analysis is effective at various instants following system contingencies. Also this method has a good performance for voltage stability Enhancement of large, complex power system networks. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system.

REFERENCES

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

[2] K. Y. Lee, Y. M. Paru, and J. L. Oritz, "A united approach to optimal real and reactive power dispatch," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-104, pp. 1147-1153, 1985.

[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*, vol. 1, pp. 175-182, 1987.

[4] N. Deeb and S. M. Shahidehpur, "Linear reactive power optimization in a large power network using the decomposition approach," *IEEE Transactions on Power System*, vol. 5, no. 2, pp. 428-435, 1990.

[5] E. Hobson, "Network consrained reactive power control using linear programming," *IEEE Transactions on Power Systems*, vol. PAS-99, no. 3, 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*, vol. 131, no, 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, pp. 1055-1063, 2002.

[9] D. Devaraj and B. Yeganarayana, "Genetic algorithm based optimal power flow for security enhancement," *IEE proc-Generation.Transmission and. Distribution*, vol. 152, no. 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] J. Holland, Adaptation in Natural and Artificial Systems, The University of Michigan Press, 1975.

[12] R. Hassan, B. Cohanim, and O. Weck. "A comparison of particle swarm optimization and the genetic algorithm," in *Proc. 46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics & Materials Conference*, Austin, Texas, 2005, pp. 18-21.

[13] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," in *Proc. IEEE International Conference on Neural Networks*, Piscataway, NJ, USA, 1995, pp. 1942-1948.

[14] R. C. Eberhart, P. K. Simpson, and R. W. Dobbins, *Computational Intelligent PC Tools*, Boston, MA, Academic Press Professional, 1966.

[15] R. C. Eberhart and Y. Shi, "Comparison between genetic algorithms and particle swarm optimization," in *Evolutionary Programming VII*, Porto, Springer, 1998, pp. 611–616.

[16] I. Rechenberg, "Evolution strategy," in *Computational Intelligence: Imitating Life*, IEEE Press, Piscataway, NJ., 1994.

[17] H. P. Schwefel, *Evolution and Optimum Seeking*, Wiley, New York, 1995.

[18] C. F. Juang, "A hybrid of genetic algorithm and particle swarm optimization for recurrent network design," vol. 34, pp. 997-1006, 2004.

[19] R. E. Perez and K. Behdinan, "Particle swarm approach for structural design optimization," *Comput. Struct.*, vol. 85, pp. 1579–1588, 2007.

[20] M. Galante, "Structures optimization by a simple genetic algorithm," in *Numerical Methods in Engineering and Applied Sciences*, Barcelona, Spain, 1992, pp. 862–870.

[21] K. Deb, Multi-Objective Optimization Using Evolutionary Algorithms, Wiley, New York, 2001.

[22] Q. H. Wu and J. T. Ma, "Power system optimal reactive power dispatch using evolutionary programming," *IEEE Transactions on Power Systems*, vol. 10, no. 3, pp. 1243-1248, 1995.

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

[24] D. Devaraj, "Improved genetic algorithm for multi–objective reactive power dispatch problem," *European Transactions on Electrical Power*, vol. 17, pp. 569-581, 2017.

[25] P. A. Jeyanthy and 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, pp. 1793-8163, August, 2010.

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