A New Improved GA and PSO Combined Hybrid Algorithm (HIGAPSO) for Solving Optimal Reactive Power Dispatch Problem.

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Abstract—**In this paper a new evolutionary learning algorithm based on a hybrid of improved real-code genetic algorithm (IGA) and particle swarm optimization (PSO) called HIGAPSO is proposed to solve the optimal reactive power dispatch (ORPD) Problem. In order to overcome the drawbacks of standard genetic algorithm and particle swarm optimization, some improved mechanisms based on non-linear ranking selection, competition and selection among several crossover offspring and adaptive change of mutation scaling are adopted in the genetic algorithm, and dynamical parameters are adopted in PSO. The new population is produced through three approaches to improve the global optimization performance, which are elitist strategy, PSO strategy and improved genetic algorithm (IGA) strategy. The effectiveness of the proposed algorithm has been compared with Gas and PSO, synthesizing a circular array, a linear array and a base station array. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system consisting 6 generator and compared other algorithms and simulation results show that HIGAPSO is more efficient than others for solution of single-objective ORPD problem.**

Index Terms—**particle swarm , improved genetic algorithm, function optimization, optimal reactive Power dispatch, power system.**

I. 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], [7]. In order to overcome these disadvantages, researches have successfully applied evolutionary and heuristic algorithms such as Genetic Algorithm (GA) [2], Differential Evolution (DE) [8] and Particle Swarm Optimization (PSO) [9]. GA is very efficient at exploring the entire search space, but it is relatively poor in finding the precise local optimal solution in the region where the algorithm converges. A new method of optimization, Particle Swarm optimization (PSO) [18]–[20], is able to accomplish the same goal as GA optimization in a new and faster way. Since PSO and GA both work with a population of solutions, combining the searching abilities of both methods seems to be a good approach. Some attempts have been made in this direction, but with a weak integration of the two strategies. Precisely, most of the times one technique has been used just as a pre-optimizer for the initial population of the other technique [21], [22]. In order to improve the speed of convergence of evolutionary algorithms, in this paper, GA and PSO are strong combined for solving optimization problems. Based on GA and PSO, a hybrid algorithm called HIGAPSO is presented. Firstly, some improved mechanisms such as non-linear ranking selection, competition and selection among several crossover offspring and adaptive change of mutation scaling are adopted in the genetic algorithm. Then, the improved genetic algorithm is combined with PSO that is improved by dynamical parameters. During each iteration, the population is divided into three parts, which are evolved with the elitist strategy, PSO strategy and the improved genetic algorithm strategy respectively. Therefore, this kind of technique can make balance between acceleration convergence and averting precocity as well as stagnation. The simulation results show the effectiveness of the algorithm in synthesizing conformal array, linear array with prescribed nulls and array with complex pattern. The proposed Algorithm is tested on IEEE30-bus system for evolution of effectiveness of it. Results obtained from HIGAPSO is compared results reported those in

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[1].Results show that proposed algorithm is more effective and powerful than other algorithms in solution of ORPD problem.

II. Formulation of ORPD Problem

The objective of the ORPD problem is to minimize one or more objective functions while satisfying a number of constraints such as load flow, generator bus voltages, load bus voltages, switchable reactive power compensations, reactive power generation, transformer tap setting and transmission line flow. In this paper and constraints are formulated taking from [1, 12] and shown as follows.

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.

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

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 θ_{ij} 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.

$$\text{Minimize VD} = \sum_{k=1}^{nl}|V_k - 1.0| \tag{2}$$

where n_l 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:

$$P_{Gi} - P_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \dots, nb \tag{3}$$

$$Q_{Gi} - Q_{Di}\, V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \dots, nb \tag{4}$$

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:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng \tag{18}$$

Load bus voltage (V_{Li}) inequality constraint:

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl \tag{19}$$

Switchable reactive power compensations (Q_{Ci}) inequality constraint:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc \tag{20}$$

Reactive power generation (Q_{Gi}) inequality constraint:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng \tag{21}$$

Transformers tap setting (T_i) inequality constraint:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \tag{22}$$

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

$$S_{Li}^{min} \leq S_{Li}^{max}, i \in nl \tag{23}$$

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

III. Hybrid of Improved GA and PSO (HIGAPSO)

The proposed HIGAPSO combines GA with PSO to form a hybrid algorithm. Due to combination of different optimization mechanisms, not only the offspring can keep diversity, but also PSO can keep the balance of global search and local search, so the entire search ability of the algorithm can be improved. In this section, improved GA and PSO are introduced first, followed by a detailed introduction of HIGAPSO.

A. Improved Genetic Algorithm

Floating-point GA uses floating-point number representation for the real variables and thus is free from binary encoding and decoding. It takes less memory space and works faster than binary GA. Some practical schemes to improve GA performance are introduced in this paper. According to the optimal results, we can conclude that these measures are effective and helpful in improving convergence property and accuracy.

B. Nonlinear Ranking Selection

Ranking methods only require the evaluation function to map the solutions to a partially ordered set. All individuals in a population are ranked from best to worst based on their fitness values. It assigns the probability of an individual based on its rank (*r*) and it is expressed as follows:

$$\begin{cases} p(r) = q'(1-q)^{r-1} \\ q' = \frac{q}{1-(1-q)^p} \end{cases} \tag{24}$$

Such that

$$\sum_{r=1}^{P} p(r) = 1 \tag{25}$$

where

q = the probability of selecting the best individual = [0, 1],

r = the rank of the individual = $\begin{cases} 1, \text{for the best individual} \\ P, \text{for the worst individual} \end{cases}$

P = the population size

It can be seen that this selection probability doesn't use the absolute value information of fitness value so that it avoid the fitness value scale transformation and control the prematurity to some extent.

C. Competition and Selection

In natural biological evolution, two parents after crossover can produce several offspring, and the competition also exists among the offspring which are produced by the same parents. Motivate by this phenomenon, we adopt competition and selection among several crossover offspring. Different from the conventional algorithm in which two parents only produce two offspring, the two parents, chromosomes as $a_s = [x_1^s, x_2^s, \ldots, x_n^s]$ and $a_t = [x_1^t, x_2^t, \ldots, x_n^t]$ in this algorithm will produce four chromosomes according to the following mechanisms [24]:

$$b_1 = [b_1^1, b_2^1, \ldots, b_n^1] = \frac{a_s + a_t}{2} \quad (26)$$

$$b_2 = [b_1^2, b_2^2, \ldots, b_n^2] = a_{max}(1-\omega) + max(a_s, a_t)\omega \quad (27)$$

$$b_3 = [b_1^3, b_2^3, \ldots, b_n^3] = a_{min}(1-\omega) + min(a_s, a_t)\omega \quad (28)$$

$$b_4 = [b_1^4, b_2^4, \ldots, b_n^4] = \frac{(a_{max}+a_{min})(1-\omega)+(a_1+a_2)\omega}{2} \quad (29)$$

$$a_{max} = [x_1^{max}, x_2^{max}, \ldots, x_n^{max}] \quad (30)$$

$$a_{min} = [x_1^{min}, x_2^{min}, \ldots, x_n^{min}] \quad (31)$$

where $\omega \epsilon$ [0, 1] denotes the weight to be determined by users, $max(a_s, a_t)$ denotes the vector with each element obtained by taking the maximum among the corresponding element of a_s and a_t.Among b_1 to b_4, the two with the largest fitness value are used as the offspring of the crossover operation. As seen from Eqs. (26) to (30), the potential offspring spreads over the domain. At the same time, (26) and (30) results in searching around the centre region of the domain, (27) and (28) can move b_2 and b_3 to be near a_{max} and a_{min} respectively. Thus, the offspring generated by this operator, is better than that obtained by arithmetic crossover or heuristic crossover.

D. Mutation

This is the unary operator responsible for the fine tuning capabilities of the system, so that it can escape from the trap of local optimum. It is defined as follows: For a parent p, if variable p_k was selected at random for this mutation, the result is:

$$\bar{P} = (P_1, \ldots, \overline{P_k}, \ldots, P_n) \quad (32)$$

$$\overline{P_k} \;=\epsilon\; \left\{max\left(P_k - \mu\frac{P_k^{max} - P_k^{min}}{2}, P_k^{min}\right), min\left(P_k + \mu\frac{P_k^{max} - P_k^{min}}{2}, P_k^{max}\right)\right\} \quad (33)$$

and P_k^{max}, P_k^{min} are upper and lower bounds of P_k respectively,μ decreased with the increase of iterations.

$$\mu(\tau) = 1 - r^{[1-(\tau/T)]^b} \quad (34)$$

where r is uniform random number in [0, 1], T is the maximum number of iterations, $\boldsymbol{\tau}$ is the current iteration number, and b is the shape parameter. From (34), at the initial stage of evolution, for small value of r, μ $(\boldsymbol{\tau}) \approx 1$, the mutation domain is large in this case. However, in the later evolution, when $\boldsymbol{\tau}$ approaches T, μ $(\boldsymbol{\tau}) \approx 0$, the mutation domain become small and search in the local domain.

IV. Particle Swarm Algorithm

The PSO conducts searches using a population of particles which correspond to individuals in GAs. The population of particles is randomly generated initially. Each particle represents a potential solution and has a position represented by a position vector $\overrightarrow{x_i}$. A swarm of particles moves through the problem space, with the moving velocity of each particle represented by a position vector $\overrightarrow{v_i}$ At each time step, a function f_i representing a quality measure is calculated by using $\overrightarrow{x_i}$ as input. Each particle keeps track of its own best position, which is associated with the best fitness it has achieved so far in a vector $\overrightarrow{p_i}$. Furthermore, the best position among all the particles obtained so far in the population is kept track of as $\overrightarrow{p_g}$. At each time step $\boldsymbol{\tau}$, by using the individual best position, $\overrightarrow{p_i}(\boldsymbol{\tau})$ and global best position, $\overrightarrow{p_g}(\boldsymbol{\tau})$a new velocity for particle i *is* updated by

$$\overrightarrow{v_i}(\boldsymbol{\tau}+\mathbf{1}) = \boldsymbol{\omega}\overrightarrow{\boldsymbol{v_i}}(\boldsymbol{\tau}) + \boldsymbol{c_1}\boldsymbol{\emptyset_1}(\overrightarrow{\boldsymbol{p_i}}(\boldsymbol{\tau})\text{-}\overrightarrow{\boldsymbol{x_i}}(\boldsymbol{\tau})) + \boldsymbol{c_2}\boldsymbol{\emptyset_2}(\overrightarrow{\boldsymbol{p_g}}(\boldsymbol{\tau}) - \overrightarrow{\boldsymbol{x_i}}(\boldsymbol{\tau})) \quad (35)$$

where $\boldsymbol{c_1}$ and $\boldsymbol{c_2}$ are acceleration constants and $\boldsymbol{\emptyset_1}$&$\boldsymbol{\emptyset_2}$ are uniformly distributed random numbers in [0, 1]. The term $\overrightarrow{v_i}$ is limited to its bounds. If the velocity violates this limit, it is set to its proper limit.

ω is the inertia weight factor and in general, it is set according to the following equation:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{T}.\boldsymbol{\tau} \quad (36)$$

where ω_{max} and ω_{min} is maximum and minimum value of the weighting factor respectively. T is the maximum number of iterations and τ is the current iteration number. Based on the updated velocities, each particle changes its position according to the following:

$$\overrightarrow{x_i}(\tau+1) = \overrightarrow{x_i}(\tau) + h(\tau)\overrightarrow{v_i}(\tau+1) \quad (37)$$

where

$$h(\tau) = h_{max} - \frac{(h_{max} - h_0).\tau}{T} \quad (38)$$

where h_{max} and h_0 are positive constants

According to (35) and (37), the populations of particles tend to cluster together with each particle moving in a random direction. The computation of PSO is easy and adds only a slight computation load when it is incorporated into IGA. Furthermore, the flexibility of PSO to control the balance between local and global exploration of the problem space helps to overcome premature convergence of elite strategy in GAs, and also enhances searching ability. The global best individual is shared by the two algorithms, which means the global best individual can be achieved by the IGA or by PSO, also it can avoid the premature convergence in PSO.

V. Hybrid of Improved GA and PSO (HIGAPSO)

The HIGAPSO maintains the integration of IGA and PSO for the entire run, which consists chiefly of genetic algorithm, combined with PSO and the sequential steps of the algorithm are given below

Step 1: Randomly initialize the population of P individuals within the variable constraint range.

Step 2: Calculate the fitness of the population from the fitness function, and order ascendingly.

Step 3: The top N individuals are selected as the elites and reproduce them directly to the next generation.

Step 4: The S individuals followed are evolved with PSO and their best positions are updated.

Step 5: The bottom individuals are evolved with IGA and produce P-S-N offspring.

Step 6: Combine the three parts as the new generation and calculate the fitness of the population. Choose the best position among all the individuals obtained so far kept as the global best.

Step 7: Repeat steps 3–6 until a stopping criterion, such as a sufficiently good solution being discovered or a maximum number of generations being completed, is satisfied. The best scoring individual in the population is taken as the final answer.

VI. Simulation Results

Proposed approach has been applied to solve ORPD problem. In order to demonstrate the efficiency and robustness of proposed HIGAPSO which is tested on standard IEEE30-bus test system .The test system has six generators at the buses 1, 2, 5, 8, 11and 13 and four transformers with off-nominal tap ratio at lines6-9, 6-10, 4-12, and 28-27 and, hence, the number of the optimized control variables is 10 in this problem.

TABLE I. Best Control Variables Settings for Different Test Cases of Proposed Approach

Control Variables setting	Case 1: Power Loss	Case 2: Voltage Deviations
VG1	1.03	0.99
VG2	1.04	0.95
VG5	1.04	1.03
VG8	1.02	1.03
VG11	1.03	1.01
VG13	0.95	1.05
VG6-9	1.00	0.90
VG6-10	1.03	1.02
VG4-12	1.03	1.04
VG27-28	1.02	0.90
Power Loss (Mw)	3.6868	3.682
Voltage deviations	0.6961	0.1892

TABLE II. Comparison of the Simulation Results for Power Loss

Control Variables Setting	HIGAPSO	GSA [23]	Individual Optimizations [1]	Multi Objective Ea [1]	As Single Objective [1]
VG1	1.03	1.049998	1.050	1.050	1.045
VG2	1.04	1.024637	1.041	1.045	1.042
VG5	1.04	1.025120	1.018	1.024	1.020
VG8	1.02	1.026482	1.017	1.025	1.022
VG11	1.03	1.037116	1.084	1.073	1.057
VG13	0.95	0.985646	1.079	1.088	1.061
T6-9	1.03	1.063478	1.002	1.053	1.074
T6-10	1.08	1.083046	0.951	0.921	0.931
T4-12	1.70	1.100000	0.990	1.014	1.019
T27-28	1.04	1.039730	0.940	0.964	0.966
Power Loss (Mw)	3.6868	4.616657	5.1167	5.1168	5.1630
Voltage Deviations	0.6961	0.836338	0.7438	0.6291	0.3142

VII. Conclusion

In this paper, one of the recently developed stochastic algorithm HIGAPSO 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 HIGAPSO approach can reveal higher quality solution for the different objective functions in this paper.

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