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Active Power Loss Reduction by Improved Particle Swarm Optimization Algorithm

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Abstract

In this paper an Improved Particle Swarm Optimization (IPSO) algorithm is proposed to solve the optimal reactive power Problem. In order to overcome the drawbacks of standard genetic algorithm (GA) and particle swarm optimization (PSO) , 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, & 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 enhanced genetic algorithm 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 efficiency of the proposed algorithm, it has been tested in standard IEEE 118 & practical 191 bus test systems and compared other algorithms. Simulation results show that real power loss considerably reduced and control variables are within the limits.

Keywords: *Particle Swarm Optimization, Genetic Algorithm, Optimal Reactive Power.*

1. Introduction

Various algorithms are employed to solve the Reactive Power problem. Dissimilar types of arithmetical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been previously used to solve the optimal reactive power problem. The voltage stability problem plays a central role in power system planning and operation [8].Evolutionary algorithms such as genetic algorithm, Hybrid differential evolution algorithm, Biogeography Based algorithm, a fuzzy based approach, an improved evolutionary programming [9-15] have been already utilized to solve the reactive power flow problem In [16-18] different methodologies are effectively handled the optimal power problem. In [19-20], a programming based approach and probabilistic algorithm is used to solve the optimal reactive power problem. In this paper an Improved Particle Swarm Optimization (IPSO) algorithm is proposed to solve the optimal reactive power Problem. Particle swarm optimization (PSO) and genetic algorithm (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 time one technique has been used just as a pre-optimizer for the initial population of the other technique. 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 enhanced 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 enhanced 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. In order to evaluate the efficiency of the proposed algorithm, it has been tested in standard IEEE 118 & practical 191 bus test systems and compared other algorithms. Simulation results show that real power loss considerably reduced and control variables are within the limits.

2. Research Method
2.1. Problem Formulation
The objective of the optimal reactive power 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.

2.1.1. 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.

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

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.

2.1.2. 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.

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

Where n_l is the number of load busses and V_k is the voltage magnitude at bus k.

2.1.3. 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:

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

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

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:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng \qquad (5)$$

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

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl \qquad (6)$$

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

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc \qquad (7)$$

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

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng \qquad (8)$$

Transformers tap setting (T_i) inequality constraint:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \qquad (9)$$

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

$$S_{Li}^{min} \le S_{Li}^{max}, i \in nl \qquad (10)$$

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

2.2. Hybridization of Genetic algorithm with Particle swarm optimization

The proposed Improved Particle Swarm Optimization (IPSO) algorithm combines Particle swarm optimization (PSO) and genetic algorithm (GA) 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.

2.2.1. 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.

1. 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:

$$\begin{cases} p(r) = q'(1-q)^{r-1} \\ q' = \frac{q}{1-(1-q)^{P}} \end{cases} \qquad (11)$$

Such that

$$\sum_{r=1}^{P} p(r) = 1 \qquad (12)$$

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.

2. 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 $a_s = [x_1^s, x_2^s, \dots, x_n^s]$and $a_t = [x_1^t, x_2^t, .., x_n^t]$ in this algorithm will produce four chromosomes according to the following mechanisms :

$$b_1 = [b_1^1, b_2^1, .., b_n^1] = \frac{a_s + a_t}{2} \qquad (13)$$

$$b_2 = [b_1^2, b_2^2, .., b_n^2] = a_{max}(1-\omega) + max(a_s, a_t)\omega \qquad (14)$$

$$b_3 = [b_1^3, b_2^3, .., b_n^3] = a_{min}(1-\omega) + min(a_s, a_t)\omega \quad (15)$$

$$b_4 = [b_1^4, b_2^4, .., b_n^4] = \frac{(a_{max}+a_{min})(1-\omega)+(a_1+a_2)\omega}{2} \quad (16)$$

$$a_{max} = [x_1^{max}, x_2^{max}, .., x_n^{max}] \quad (17)$$

$$a_{min} = [x_1^{min}, x_2^{min}, .., x_n^{min}] \quad (18)$$

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. (13) to (17), the potential offspring spreads over the domain. At the same time, (13) and (17) results in searching around the centre region of the domain, (14) and (15) 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.

3. 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:

$$\bar{P} = (P_1, .., \overline{P_k}, .., P_n) \quad (19)$$

$$\overline{P_k} = \epsilon\left\{max\left(P_k - \mu\frac{P_k^{max} - P_k^{min}}{2}, P_k^{min}\right), min\left(P_k + \mu\frac{P_k^{max} - P_k^{min}}{2}, P_k^{max}\right)\right\} \quad (10)$$

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

$$\mu(\tau) = 1 - r^{[1-(\tau/T)]^b} \quad (11)$$

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 (11), at the initial stage of evolution, for small value of *r*, $\mu(\boldsymbol{\tau}) \approx 1$, the mutation domain is large in this case. However, in the later evolution, when $\boldsymbol{\tau}$ approaches *T*, $\mu(\boldsymbol{\tau}) \approx 0$, the mutation domain become small and search in the local domain.

2.2.2. 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 $\vec{x_i}$. A swarm of particles moves through the problem space, with the moving velocity of each particle represented by a position vector$\vec{v_i}$ At each time step, a function f_i representing a quality measure is calculated by using $\vec{x_i}$ 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 $\vec{p_i}$. Furthermore, the best position among all the particles obtained so far in the population is kept track of as $\vec{p_g}$. At each time step $\boldsymbol{\tau}$, by using the individual best position, $\vec{p_i}(\boldsymbol{\tau})$ and global best position, $\vec{p_g}(\boldsymbol{\tau})$a new velocity for particle i *is* updated by

$$\vec{v_i}(\boldsymbol{\tau}+\mathbf{1}) = \boldsymbol{\omega}\vec{\boldsymbol{v_i}}(\boldsymbol{\tau}) + \boldsymbol{c_1}\emptyset_1(\vec{\boldsymbol{p_i}}(\boldsymbol{\tau}) - \vec{\boldsymbol{x_i}}(\boldsymbol{\tau})) + \boldsymbol{c_2}\emptyset_2(\vec{\boldsymbol{p_g}}(\boldsymbol{\tau}) - \vec{\boldsymbol{x_i}}(\boldsymbol{\tau})) \quad (12)$$

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 $\vec{v_i}$ 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:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{T} . \boldsymbol{\tau} \quad (13)$$

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:

$$\vec{x_i}(\tau+1) = \vec{x_i}(\tau) + h(\tau)\vec{v_i}(\tau+1) \qquad (14)$$

Where

$$h(\tau) = h_{max} - \frac{(h_{max}-h_0).\tau}{T} \qquad (15)$$

Where h_{max} and h_0 are positive constants

According to (12) and (14), 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 GA. 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. Also it can avoid the premature convergence in PSO.

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 GA 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.

3. Results and Analysis

At first Improved Particle Swarm Optimization (IPSO) algorithm has been tested in standard IEEE 118-bus test system [28].The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95 -1.1 per-unit., and on load buses are 0.95 -1.05 per-unit. The limit of transformer rate is 0.9 -1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 1, with the change in step of 0.01.

Table 1. Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results have been listed in Table 2 and the results clearly show the better performance of proposed Improved Particle Swarm Optimization (IPSO) algorithm.

Table 2. Comparison results

Active power loss (p.u)	**BBO [29]**	**ILSBBO/ strategy1 [29]**	**ILSBBO/ strategy1 [29]**	**Proposed IPSO**
Min	128.77	126.98	124.78	106.52
Max	132.64	137.34	132.39	112.68
Average	130.21	130.37	129.22	108.38

Then the Improved Particle Swarm Optimization (IPSO) algorithm has been tested in practical 191 test system and the following results have been obtained. In Practical 191 test bus system – Number of Generators = 20, Number of lines = 200, Number of buses = 191 Number of transmission lines = 55. Table 3 shows the optimal control values of practical 191 test system obtained by IPSO method. And table 4 shows the results about the value of the real power loss by obtained by Improved Particle Swarm Optimization (IPSO) algorithm.

Table 3. Optimal Control values of Practical 191 utility (Indian) system by IPSO method

VG1	1.10		VG 11	0.90
VG 2	0.76		VG 12	1.00
VG 3	1.01		VG 13	1.00
VG 4	1.01		VG 14	0.90
VG 5	1.10		VG 15	1.00
VG 6	1.10		VG 16	1.00
VG 7	1.10		VG 17	0.90
VG 8	1.01		VG 18	1.00
VG 9	1.10		VG 19	1.10
VG 10	1.01		VG 20	1.10

T1	1.00		T21	0.90		T41	0.90
T2	1.00		T22	0.90		T42	0.90
T3	1.00		T23	0.90		T43	0.91
T4	1.10		T24	0.90		T44	0.91
T5	1.00		T25	0.90		T45	0.91
T6	1.00		T26	1.00		T46	0.90
T7	1.00		T27	0.90		T47	0.91
T8	1.01		T28	0.90		T48	1.00
T9	1.00		T29	1.01		T49	0.90
T10	1.00		T30	0.90		T50	0.90
T11	0.90		T31	0.90		T51	0.90
T12	1.00		T32	0.90		T52	0.90
T13	1.01		T33	1.01		T53	1.00
T14	1.01		T34	0.90		T54	0.90
T15	1.01		T35	0.90		T55	0.90
T19	1.02		T39	0.90			
T20	1.01		T40	0.90			

Table 4. Optimum real power loss values obtained for practical 191 utility (Indian) system by IPSO method.

Real power Loss (MW)	**IPSO**
Min	138.128
Max	144.146
Average	140.162

4. Conclusion

In this paper, Improved Particle Swarm Optimization (IPSO) algorithm successfully solved the optimal reactive power problem. The proposed algorithm combines Particle swarm optimization (PSO) and genetic algorithm (GA) 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 order to evaluate the efficiency of the proposed algorithm, it has been tested in standard IEEE 118 & practical 191 bus test systems and compared other algorithms. Simulation results show that real power loss considerably reduced and control variables are within the limits.

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