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Combination of Immune Genetic Particle Swarm Optimization algorithm with BP Algorithm to Solve Optimal Reactive Power Dispatch Algorithm

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***Abstract*: In this paper, merging Immune Genetic Particle Swarm Optimization algorithm (IGPSO) with BP algorithm to optimize BP Neural Network parameter i.e., BPIGPSO amalgamation to solve optimal reactive power dispatch algorithm. The basic perception is that first training BP neural network with IGPSO to find out a comparatively optimal solution, then take the network parameter at this time as the preliminary parameter of BP algorithm to carry out the training, finally searching the optimal solution. The proposed BPIGPSO has been tested on standard IEEE 57 bus test system and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss.**

***Keywords:* BP neural network, Immune Genetic Particle Swarm Optimization algorithm, Optimal Reactive Power, Transmission loss.**

I. INTRODUCTION

Reactive power optimization places a significant role in optimal operation of power systems. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been implemented to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the intricacy in managing inequality constraints. The problem of voltage stability and collapse play a key role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is projected to increase the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to elucidate the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to calculate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes Immune Genetic Particle Swarm Optimization algorithm (IGPSO) with BP algorithm to optimize BP Neural Network parameter i.e., BPIGPSO amalgamation [21-26] to solve reactive power dispatch problem. The basic idea is that first training network with IGPSO to find out a reasonably optimal solution, and then take the network parameter as the chief parameter of network in BP algorithm to carry out the training, lastly searching the optimal solution. Basic difficulties need to be solved by combination training algorithm are encoding of particles, creation of fitness function, modernizing of particles speed and position, enhancement on particle swarm optimization by using immunization information treating mechanism, grouping of optimal particles and BP algorithm. The proposed BPIGPSO algorithm has been evaluated on standard IEEE 57, bus test system. The simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

II. PROBLEM FORMULATION

The OPF problem is considered as a common minimization problem with constraints, and can be written in the following form:

Minimize f(x, u) (1)

Subject to g(x,u)=0 (2)

and

$h(x, u) \leq 0$ (3)

Where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \quad (4)$$

The control variables are the generator bus voltages, the shunt capacitors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \quad (5)$$

or

$$u = \left(V_{g1}, \dots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \quad (6)$$

Where Ng, Nt and Nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

III. OBJECTIVE FUNCTION

A. Active power loss

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be mathematically described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (7)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (8)$$

Where g_k : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

B. Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (9)$$

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (10)$$

C. Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \qquad (11)$$

D. Inequality Constraints

The inequality constraints h(x,u) imitate the limits on components in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \qquad (12)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \qquad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \qquad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \qquad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \qquad (16)$$

Where N is the total number of buses, N_T is the total number of Transformers; N_c is the total number of shunt reactive compensators.

IV. BP NEURAL NETWORK ALGORITHM

BP neural network evaluation technique makes use of its robust capability in processing nonlinear problems to carry out evaluation of online education performance. This technique has advantages like self-learning, strong fault tolerance and adaptability; however, the algorithm is easy to be trapped into defects like local minimum, over-learning, strong operation specialization. The theory of BP neural network is compacted in basis, rigorous in derivation, clear in physical concept and strong in generalization. However, BP algorithm is the steepest descent method based on gradient, taking square error as objective function, so there unavoidably have the following four great defects: training easy to fall into local minimum, learning process slow in rate of convergence, structure of network difficult to be established, generalization ability of designed network unable to be guaranteed, which intensely influence the further development and application of BP neural network.

V. BP NEURAL NETWORK ALGORITHM IMPROVEMENT WITH IGPSO ALGORITHM

Immune Genetic Particle Swarm Optimization algorithm (IGPSO) with BP algorithm to optimize BP Neural Network parameter i.e., BPIGPSO amalgamation training algorithm.

A. Encoding of particles

Learning method of BP neural network is to carry out optimization study on such two incessant parameters of network as weight and threshold. As the preliminary value is tough to be confirmed, this paper adopts IGPSO to decide the primary parameter values of network. In the encoding process of particles, if binary encoding is adopted on parameters, the encoding string will be too long and shall be reverted to real numbers while decoding, thus inducing the learning accurateness of network and the running time of algorithm. Therefore, this theory adopts real number encoding form, i.e., code string form, as shown in equation (17), in which $V = (v_1, v_2, \ldots, v_D)$, X symbolizes the position of particles, V represents the speed of particles, D represents the total number of optimal network parameters; D can be obtained through equation (18):

$$X = (w_{n1}, .., w_{n2}, \theta_1, .., \theta_{n1}, w_{m1}, .., w_{mn1}, \theta_1', .., \theta_m') \qquad (17)$$

$$D = n * n_1 + n_{1*}m + n_1 + m \qquad (18)$$

B. Development of fitness function

PSO algorithm fundamentally makes no use of external information in the evolution probing, only taking fitness function as reference, making use of the fitness value of each individual in the group to carry out searching, judging the superiority of individuals with fitness value. Therefore, it is serious to choose fitness function, directly inducing the rate of convergence of PSO algorithm and whether able to find optimal solution. Generally, fitness function is altered from objective function. This study defines the network error as equation (19). Error function is also the objective function in this theory. As the small the objective function value is, the larger the fitness value is and the larger the objective function value is, the smaller the fitness value is, fitness function shall take the reciprocal of objective function, i.e., fitness function as shown equation (20):

$$E_A = \sum_{p-1}^{P} E^{(P)} = \frac{1}{2}\sum_{p-1}^{P}\sum_{k-0}^{m-1}\left(d_k^{(p)} - y_k^{(p)}\right)^2 \qquad (19)$$

$$F(E_A) = 1/E_A \qquad (20)$$

C. Updating of particles speed and position

PSO algorithm first initializes a collection of arbitrary particles, then find out optimal solution through iterations. During each iteration, particles modernize themselves through tracking two “extreme”, i.e., individual extreme P_i and global extreme P_g. Suppose that the initialized group size is N, the position of the ith particle in the d th dimension is x_{id}, flying speed is v_{id}, the optimal position searched by it at present is p_{id}, the optimal position searched by the entire particle swarm at present is p_{gd}, then the algorithm formulation for the updating of particles position and speed is given by equation (21) :

$$\begin{cases} V_i^{k+1} = x\begin{pmatrix} V_i^k + C_1 * r_1 * (P_i^k - X_i^k) \\ +C_2 * r_2 * (P_g^k - X_i^k) \end{pmatrix} \\ X_i^{k+1} = X_i^k + V_i^{k+1} \\ w = w_{max} - \frac{w_{max}-w_{min}}{num_{max}} * num \end{cases} \qquad (21)$$

In which $w_{\max}$ and $w_{\min}$ represent the maximum and minimum values of w, respectively, $num_{\max}$ and num are largest iterations and current iteration, respectively, $v_{id} \in [-v_{max}, v_{max}]$, x is constriction. According to application experience, $x = 0.729$, $c_1 = c_2 = 2.05$, r_1 and r_2 are arbitrary numbers among (0, 1), $v_{\max}$ is constant which is set by users; termination condition of iteration, according to specific problems, is generally the largest iterations or that the optimal position searched by particle swarm up till now meeting the presumed minimum threshold.

D. Improving PSO by immunization information procedure

Immunological memory means that immune system often saves the antibody intruding antigen reaction part as memory cells. While the antigens of the same kind re-intrude, memory cells will be stimulated and produce large amount of antibodies. In IGPSO, this idea is used for saving outstanding particles, inspecting relatively outstanding particles created during the process of each iteration as memory cells. While new-fangled particles are tested to not imitate to the requirements, it is considered that it is very low in fitness and shall be substituted by memory cells. Immunological regulation mechanism means that it will be endorsed while the affinity of antibodies and antigens is large or low in concentration, while it will be restrained while the affinity of antibodies and antigens is small or high in concentration and different antibodies keep certain concentration all along. Such topographies are used for selecting new-fangled particles in IGPSO.Test the newly created N particles, if the position of particles is infeasible solution, i.e., certain-dimensional component of X is not within the entitled scope, substitute with memory particles. Arbitrarily create M new particles meeting requirements. Re-select N particles according to affinity and concentration of antibodies and antigens. While training BP network, the greater the fitness of particles (antibodies) is, the stronger the affinity is and the lower the fitness is, the poorer the affinity is. Hence, affinity can be articulated with the reciprocal of fitness function, as shown in equation (22), selection probability determined by affinity as shown in equation (23), concentration of particles can be calculated with fitness by using equation (24), selection probability determined by concentration as shown in equation (25), probability for particles to be selected can be obtained through equation (26), in which $i = 1, 2, \ldots, M + N$, α is a weight coefficient among (0, 1); $M + N$ particles can be ordered according to P_i, the first N particles with large P_i values will be selected:

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$$Q_i = {}^{1}/_{F_i} \quad (22)$$

$$P_{i1} = Q_i/\sum_{U-1}^{M+N} Q_u \quad (23)$$

$$D_i = 1/\sum_{u-1}^{M+N}|F_i - F_u| \quad (24)$$

$$P_{i2} = D_i^{-1}/\sum_{u-1}^{M+N} D_u^{-1} \quad (25)$$

$$P_i = \alpha P_{i1} + (1-\alpha)P_{i2} \quad (26)$$

In immune system, vaccines are a kind of estimate on certain gene of optimal antibody, based on people's more or less priori knowledge on elucidating problems and extracting characteristic information. Vaccination is to alter certain components of antibodies according to vaccines. Immunization selection is used to check the performance of antibodies through vaccination. If the fitness is not as worthy as paternal generation after vaccination, the paternal generation shall be kept; if the fitness is better than paternal generation after vaccination, then choosing whether substitute its paternal generation through probability. In IGPSO, p_g produced in every iteration can be considered to be the most closed to the optimal solution, taking its definite component as vaccine to carry out vaccination and selection on particles. Techniques are as follows:

(i) Arbitrarily draw a particle from N new particles, and then arbitrarily draw a component in p_g and interchange with the drawn particle in corresponding position, finish one vaccination.

(ii) Check whether the vaccinated particle meets the constraint conditions, abandon if not; carry out fitness calculation if yes. If the fitness is less than that before vaccination, then abandon; or else, carry out probability calculation. While calculating probability, arbitrarily generate a number through Rand ( ) to compare with threshold p_g, selection the particle if it is larger, or else, abandon.

(iii)After q times of looping execution (i.e., q times of vaccination) on the above vaccines and immunization selection, produce new-generation N particles and carry out next iteration.

(iv) After training through IGPSO, find out p_g particle, decoding each component in p_g into corresponding parameter values, then train with BP algorithm until the algorithm meeting termination conditions.

VI. BPIGPSO ALGORITHM TRAINING STEPS

1. Arbitrarily initialize N particles according to parameter setting.

2. Compute the fitness of each particle in the group and save the particle with optimal fitness as memory particle.

3. Produce new N particles according to equation 21.

4. Check each particle in particle group, substitute with memory particles if not meeting conditions; or else, turn to the 5th step.

5. Arbitrarily generate M particles, select N particles in $M+N$ particles according to affinity and concentration.

6. Re-generate new N particles according to vaccination and immunization selection mechanism.

7. Go to the 8th step if reaching the set evolution generation or current optimal particle meeting conditions; or else, go to the 2nd step.

8. Decode the optimal particle in the 7th step into network parameter to oblige as the preliminary parameter of BP network.

9. Alter current network parameters with BP algorithm.

10Terminate if reaching the termination condition of BP algorithm; or else, go to the 9th step.

VII. SIMULATION RESULTS

The proposed BPIGPSO algorithm for solving ORPD problem is tested in standard IEEE-57 bus power system. The IEEE 57-bus system data consists of 80 branches, 7 generator-buses and 17 branches under load tap setting transformer branches. The possible reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. In this case, the search space has 27 dimensions, i.e., the seven generator voltages, 17

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transformer taps, and three capacitor banks. The system variable limits are given in Table I. The preliminary conditions for the IEEE-57 bus power system are given as follows:

P_{load} = 12.425 p.u. Q_{load} = 3.337 p.u.

The total initial generations and power losses are obtained as follows:

$\sum P_G$ = 12.7728 p.u. $\sum Q_G$ = 3.4559 p.u.

P_{loss} = 0.27445 p.u. Q_{loss} = -1.2248 p.u.

Table II shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after BPIGPSO based optimization which are within their acceptable limits. In Table III, a comparison of optimum results obtained from proposed BPIGPSO with other optimization techniques for optimal reactive power dispatch (ORPD) problem mentioned in literature for IEEE-57 bus power system is given. These results indicate the robustness of proposed BPIGPSO approach for providing better optimal solution in case of IEEE-57 bus system.

TABLE I: VARIABLES LIMITS FOR IEEE-57 BUS POWER SYSTEM (P.U.)

REACTIVE POWER GENERATION LIMITS							
BUS NO	1	2	3	6	8	9	12
Q_{GMIN}	-1.1	-.010	-.01	-0.01	-1.1	-0.02	-0.2
Q_{GMAX}	1	0.1	0.1	0.23	1	0.01	1.50
VOLTAGE AND TAP SETTING LIMITS							
V_{GMIN}	V_{GMAX}	V_{PQMIN}	V_{PQMAX}	T_{KMIN}	T_{KMAX}		
0.5	1.0	0.91	1.01	0.5	1.0		
SHUNT CAPACITOR LIMITS							
BUS NO	18	25	53				
Q_{CMIN}	0	0	0				
Q_{CMAX}	10	5.1	6.2				

TABLE II: CONTROL VARIABLES OBTAINED AFTER OPTIMIZATION BY BPIGPSO METHOD FOR IEEE-57 BUS SYSTEM (P.U.).

Control Variables	BPIGPSO
V1	1.1
V2	1.063
V3	1.058
V6	1.048
V8	1.060
V9	1.037
V12	1.045
Qc18	0.0849
Qc25	0.334
Qc53	0.0627
T4-18	1.019
T21-20	1.052
T24-25	0.966
T24-26	0.933

T7-29	1.076
T34-32	0.937
T11-41	1.014
T15-45	1.059
T14-46	0.923
T10-51	1.037
T13-49	1.058
T11-43	0.919
T40-56	0.905
T39-57	0.963
T9-55	0.978

TABLE III: COMPARATIVE OPTIMIZATION RESULTS FOR IEEE-57 BUS POWER SYSTEM (P.U.)

S.No.	Optimization Algorithm	Best Solution	Worst Solution	Average Solution
1	NLP [27]	0.25902	0.30854	0.27858
2	CGA [27]	0.25244	0.27507	0.26293
3	AGA [27]	0.24564	0.26671	0.25127
4	PSO-w [27]	0.24270	0.26152	0.24725
5	PSO-cf [27]	0.24280	0.26032	0.24698
6	CLPSO [27]	0.24515	0.24780	0.24673
7	SPSO-07 [27]	0.24430	0.25457	0.24752
8	L-DE [27]	0.27812	0.41909	0.33177
9	L-SACP-DE [27]	0.27915	0.36978	0.31032
10	L-SaDE [27]	0.24267	0.24391	0.24311
11	SOA [27]	0.24265	0.24280	0.24270
12	LM [28]	0.2484	0.2922	0.2641
13	MBEP1 [28]	0.2474	0.2848	0.2643
14	MBEP2 [28]	0.2482	0.283	0.2592
15	BES100 [28]	0.2438	0.263	0.2541
16	BES200 [28]	0.3417	0.2486	0.2443
17	Proposed BPIGPSO	0.22349	0.23468	0.23116

VIII. CONCLUSION

In this paper, the BPIGPSO has been efficaciously implemented to solve Optimal Reactive Power Dispatch problem. The projected algorithm has been tested on the standard IEEE 57 -bus system. The results are compared with other heuristic methods and the proposed algorithm demonstrated its efficiency and strength in minimization of real power loss and also various system control variables are well within the acceptable limits .

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