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Active Power Loss Reduction by Customized Particle Swarm Optimization Algorithm

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ABSTRACT

This paper presents Customized Particle swarm optimization (CPSO) algorithm for solving optimal reactive power problem. The standard Particle Swarm Optimization (PSO) algorithm is an innovative evolutionary algorithm in which each particle studies its own previous best solution and the group's previous best to optimize problems. It is well known that the advance-and-retreat strategy is a simple and operative method of one-dimensional search. Advance-and-retreat strategy has been used to bestow the clones with faster speed to find nearby local regions before subsequent clonal operation. Besides, in the next clonal operation, the search space is enlarged prominently and the diversity of clones is augmented. When the fitness value becomes better at last 'flying', then the cloned particle will progresses. On the divergent, the cloned particle retreats then searches in the back direction of the last "flying" with a small step-size of the preceding velocity. Thus, the swarm has robust optimization capability. In order to evaluate the efficiency of proposed algorithm, it has been tested on IEEE 30 bus system and compared to other algorithms. Simulation results demonstrate good performance of the Customized Particle swarm optimization (CPSO) algorithm in solving an optimal reactive power problem.

Keywords *Advance and retreat strategy, clone mechanism, Particle swarm optimization, Swarm Intelligence, optimal reactive power, Transmission loss.*

INTRODUCTION

Main objective of optimal reactive power problem is to minimize the real power loss and bus voltage deviation. Various mathematical techniques like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the complexity in managing inequality constraints. If linear programming is applied then the input-output function has to be uttered as a set of linear functions which mostly lead to loss of accuracy. The problem of voltage stability and collapse play a major role in power system planning and operation [8]. Global optimization has received extensive research awareness, and a great number of methods have been applied to solve this problem. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9, 10]. Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [11], Genetic algorithm has been used to solve optimal reactive power flow problem. In [12], Hybrid differential evolution algorithm is proposed to improve 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 solve 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 evaluate 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 presents Customized Particle swarm optimization (CPSO) algorithm for solving optimal reactive power problem. The particle swarm optimization (PSO) developed by Eberhart and Kennedy in 1995 is a stochastic global optimization technique enthused by social behaviour of bird flocking, fish schooling, or animals herding where these swarms search for food in a collective manner [21], [22]. Each particle in the swarm adjusts its search patterns to search for the comprehensive optimum in the high dimensional space by learning from its own experience and others. Since the PSO comprises a very simple concept and paradigms can be applied more easily with it, it has been proved in certain instances that PSO outperforms other population based evolutionary computing algorithms in many practical engineering fields such as function optimization ,artificial neural network training, fuzzy system control, blind source separation as well as machine learning [23].Furthermore, the PSO has also been found to be strong and reckless in solving nonlinear, non-differentiable and multi-modal problems [24].In modern years, there have been a number of efforts to combine PSO algorithms with other techniques in order to progress the performance of the conventional standard PSO.

Convergent speed, global exploration capability, and complication are the main evaluation catalogues for PSO and its variants. In this paper, the Advance and Retreat strategy is presented for the first time into the conventional standard PSO united with the Clonal mechanism, resulting in building a fresh variant of PSO. After each clonal process, the advance and retreat strategy bestows the clones with faster speed to find nearby local regions by using the history information of each particle's last performance of 'flying'. In the next clonal operation, clonal mutation and selection of the best individual of a number of subsequent generations expand the search space significantly and intensification the diversity of clones to avoid being trapped in local minima. Thus, the clones have more probabilities to find and flee the nearby local regions with faster speed. In order to evaluate the efficiency of proposed Customized Particle swarm optimization (CPSO) algorithm, it has been tested on IEEE 30 bus system and compared to other reported standard algorithms.

PROBLEM FORMULATION

The optimal power flow problem is treated as a general minimization problem with constraints, and can be mathematically written in the following form:

$$\text{Minimize } f(x, u) \tag{1}$$

$$\text{subject to } g(x,u)=0 \tag{2}$$

$$\text{and } h(x, u) \leq 0 \tag{3}$$

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:

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

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

$$u = \left(V_g, T, Q_c\right)^T \tag{5}$$

or

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

Where ng, nt and nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

OBJECTIVE FUNCTION

Active Power Loss

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

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

or

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

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.

Voltage Profile Improvement

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

$$F = PL + \omega_v \times VD \tag{9}$$

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

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

Equality Constraint

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

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

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

Inequality Constraints

The inequality constraints h(x, u) reflect 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:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \quad (12)$$

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

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (15)$$

Upper and lower bounds on the compensators reactive powers:

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

Where N is the total number of buses, NT is the total number of Transformers; Nc is the total number of shunt reactive compensators.

Particle Swarm Optimization (PSO)

The particle swarm procedure is stochastic in nature; it uses a velocity vector to update the current position of each particle in the swarm. The velocity vector is updated based on the memory gained by each particle, theoretically similar to a narrative memory, as well as the knowledge gained by the swarm as a whole. Thus, the position of each particle in the swarm is updated based on the social behaviour of the swarm which acclimatises to its environment by returning to talented regions of the space previously exposed and probing for improved positions over time. Mathematically, the position of the i^{th} particle, Xi, at iteration t + 1 is updated as follows:

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (17)$$

Where V_i^{t+1} is the corresponding updated velocity vector given as follows,

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 (P_i^t - X_i^t) + c_2 r_2 (G_{best}^t - X_i^t) \quad (18)$$

Where V_i^t is the velocity vector at iteration t, r1 and r2 represents arbitrary numbers between 0and 1; P_i^t represents the best ever particle position of particle i, and G_{best}^t corresponds to theglobal best position in the swarm up to iteration t. The remaining terms are problem dependent parameters; in this paper, cognitive parameter, c1, and c2, social parameter, are considered to be equal to 2. Also, ω is the inertia weight which plays an important role in the PSO convergence performance.

Due to the importance of ω in achieving efficient search behaviour the optimal updating criterion is taken as follows:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{k_{max}} \cdot k \quad (19)$$

Where ω_{max} and ω_{min} are the maximum and minimum values of ω, respectively. Also, k_{max}, and k are the number of maximum iterations and the number of present iteration.

Modifications in PSO

In [25], Tan et al. presented the immunity-clonal strategies into the PSO. By cloning the best individual often succeeding generations, CPSO can promise to uphold the respectable performance of standard PSO. In the interim, the core of the clonal operator is to produce a new particle swarm near the capable candidate solution according to the value of the fitness function such that the search space are enlarged significantly and the diversity of clones is augmented to avoid trapping in local minima. In [26], golden section search algorithm is united with particle swarm optimization algorithm together. The PSO is accountable for search direction, and the golden section search algorithm takes responsibility of step-size along this direction. After the search direction of a particle is determined by the velocity equation of PSO, the golden section algorithm is engaged to speed up the convergence along this direction. In PSO-LS [27], each particle has a chance of self improvement by applying local search algorithm before it connects information with other particles in the swarm. Then these basic PSO-LS are altered by selecting some precise good particles initial solutions for local search. In the local search, hill-climbing algorithms are amalgamated into particle swarm optimization to progress the performance of PSO. The genetic algorithm is united with local search in the hybrid algorithm. HGPSO (hybrid Gradient descent PSO) [28] algorithm makes use of gradient information to attain faster convergence. The gradient descent rule is united with the equation of the initial PSO to escape from local minima traps. Multi-Local PSO algorithm [29] uses gradient descent directions in order to drive each particle to a neighbour local minimum, thus discovering several solutions.

Principle of Conventional Advance and Retreat Strategy

The conventional advance and retreat strategy is a simple and operative method for the problem of one-dimensional search. One-dimensional search is also called linear search for optimization of a single-variable objective function. The iterative formula in one-dimension search is as follows:

$$x_{k+1} = x_k + v_k d_k \tag{20}$$

Where x_k denotes the position of a solution, v_k denotes the velocity of a solution and d_k denotes the direction of the velocity. The bottleneck problem in Eq. (20) is to define the exploration direction d_k and the step size v_k. Let

$$\varphi(v_k) = f(x_k + v_k d_k) \tag{21}$$

Where $\varphi(v_k)$ denotes the function value of the velocity vk, f is the objective function. The determination of the step size vk and the exploration direction dk satisfying Eq.(22) is the one-dimensional search problem.

$$\varphi(v_k) < \varphi(0) \tag{22}$$

The one-dimensional search is also called optimal one dimensional search and the step-size v_k is called optimal step-size if the step-size v_k minimizes the objective function along the exploration direction d_k as in Eqs.(23) and (24).

$$f(x_k + v_k d_k) = \min f(x_k + v d_k), \text{where } v > 0 \tag{23}$$

Or

$$\varphi(v_k) = \min \varphi(v), \text{where } v > 0 \tag{24}$$

Advance and Retreat Algorithm

Step1 Initialization: $v_0 \in [0,\infty]$, $h_0>0$, and the factor of

Acceleration $\alpha > 1$, calculate $\varphi(v_0)$, k=0.

Step2 Evaluations of the Fitness Values:

$v_{k+1} = v_k + h_k$

$\varphi_{k+1} = \varphi(v_{k+1})$

if $\varphi_{k+1} < \varphi_k$ then

go Step3

else

go Step 4

end if

Step3 Advance:

$h_{k+1} = \alpha h_k$

$v = v_k$

$v_k = v_{k+1}$

$\varphi_k = \varphi_{k+1}$

$k = k + 1$

go Step 2

Step4 Retreat:

If k = 0 then

$h_k = -h_k$ //inverse the exploration direction

$v_k = v_{k+1}$

go Step 2

else

stop

end if

Step 5:

$a = \min\{v, v_{k+1}\}$

$b = \max\{v, v_{k+1}\}$

output [X,Y]

Customized Particle Swarm Optimization (CPSO) Algorithm

Clonal Mechanism

After numerous iterations, a clonal operator is used to clone the best individual of n succeeding generations as n same particles in the solution space according to their fitness values at first, then N (size of swarm) new particles are produced via clonal mutation and selection processes. Fleetingly, the clonal operator in our Customized Particle swarm optimization (CPSO) algorithm concise as follows,

Step 1: Initialization.

Step 2: The state evolution of particles is iteratively restructured according to Eqs. (17), (18) and (28).

Step 3: Memory the global best-fit particle of each generation, PgB, as a mother particle of the clonal operator in Step 4.

Step 4: After n generations, clone the memorized n global best particles, $P_{gB}^{(i)}$,i= 1,..,n.

Step 5: Mutation Procedure: all of the cloned particles are mutated to some levels to distinguish with original or mother particle by using some arbitrary disturbances such as Gaussian noise. Assume P_{gBk} be the k-th entry of the vector P_{gB} and μ is a Gaussian arbitrary variable with zero mean and unity variance, then one can have the following arbitrary mutation procedure.

$$P_{gBk} + s * (1 - \mu) * V_{max} \tag{25}$$

Where s is the scale of mutation and V_{max} is the maximum velocity.

Step 6: Selection Procedure: We pile the current $P_{gB}^{(M)}$ in memory, but the other particles are selected according to an approach of the diversity keeping of the concentration mechanism so that in next generation of particles, a certain concentration of particles will be upheld for each fitness layer. Here the attentiveness of *i*-th particle is defined as follows.

$$D(x_i) = \left(\sum_{j=1}^{N+M} |f(x_i) - f(x_j)|\right)^{-1}, i = 1,2,..,N + M \tag{26}$$

Where x_i and $f(x_i)$ in Eq.(26) denote the i-th particle and its fitness value, respectively. Rendering to above Eq. (26), one can derive a selection probability in terms of the concentration of particles as,

$$p(x_i) = \frac{\frac{1}{D(x_i)}}{\sum_{j=1}^{N+M} \frac{1}{D(x_j)}}, i = 1,2,..,N + M \tag{27}$$

Step 7: The algorithm can be completed by some common stop criteria such as a given maximum number of fitness value evaluations or a presetting accuracy of the solution.

Advance-and-Retreat Strategy

In each iteration, we use the advance-and-retreat strategy to substitute the first part (previous velocity of a particle) of Eq. (18) in PSO just for the cloned particles. When fitness value turns superior at last 'flying', then the cloned particle will progresses according to Eq. (18). When the fitness value turns shoddier after last 'flying', the cloned particle retreats then explorations in the reverse direction of the last "flying" with a smaller step-size of the preceding velocity, which can be expressed as

$$V_{id}(t + 1) = \omega(-\alpha V_{id}(t)) + c_1 r_1 (P_{iBd}(t) - X_{id}(t)) + c_2 r_2 \left(P_{gBd}(t) - X_{id}(t)\right) \text{ where } \alpha < 1 \tag{28}$$

With the inertia weight ω declining with the evolution of the swarm, clones may be controlled in a diminishing local area for searching nearby local minima. Due to the impact of the global and the local best positions, clones alter their tracks arbitrarily. Strikingly, we just use the advance-and retreat strategy for the cloned particles. Thus, the clones do not sprinkle over the exploration space, but fly toward the nearby local region rapidly. Therefore; the advance and retreat strategy empowers each clone to forecast the next direction to the local optimum conferring to its own history information rather than just memorizing the last velocity without any conclusion of the last 'flying'. In this way, the individual convergent capability of clone is improved greatly by using the history information of each particle's last 'flying' to restrict particles searching in the space around nearby local optimum. The proposed Customized Particle swarm optimization (CPSO) algorithm doesn't need to stop the sprouting of the swarm to execute local search. Furthermore, the Customized Particle swarm optimization (CPSO) algorithm doesn't need to compute the gradient which is computationally expensive and change the structure of the traditional PSO. In particular, the clonal operator produces a new particle swarm near the favourable candidate solution according to the value of the fitness function such that the exploration space are enlarged significantly and the diversity of clones is augmented to avoid being trapped in local minima. Through keeping the clones, the proposed improved algorithm also expands the exploration space significantly to avoid trapping in local minima. Meanwhile, the core of the advance-and-retreat strategy is to speed up clones finding nearby minima in an enlarged indefinite space. Convergence rate and performance could be elevated significantly.

SIMULATION RESULTS

Validity of Customized Particle swarm optimization (CPSO) algorithm has been verified by testing in IEEE 30-bus, 41 branch system and it has 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is taken as slack bus and 2, 5, 8, 11 and 13 are considered as PV generator buses and others are PQ load buses. Control variables limits are given in Table 1.

Table1. *Primary Variable Limits (Pu)*

Variables	Min.	Max.	Category
Generator Bus	0.95	1.1	Continuous
Load Bus	0.95	1.05	Continuous
Transformer-Tap	0.9	1.1	Discrete
Shunt Reactive Compensator	-0.11	0.31	Discrete

In Table 2 the power limits of generators buses are listed.

Table2. *Generators Power Limits*

Bus	Pg	Pgmin	Pgmax	Qgmin	Qmax
1	96.00	49	200	0	10
2	79.00	18	79	-40	50
5	49.00	14	49	-40	40
8	21.00	11	31	-10	40
11	21.00	11	28	-6	24
13	21.00	11	39	-6	24

Table 3 shows the proposed CPSO approach successfully kept the control variables within limits.Table 4 narrates about the performance of the proposed CPSO algorithm. Table 5 list out the overall comparison of the results of optimal solution obtained by various methods.

Table3. *After optimization values of control variables*

Control Variables	CPSO
V1	1.0238
V2	1.0226
V5	1.0221
V8	1.0264
V11	1.0401
V13	1.0498
T4,12	0.00
T6,9	0.00
T6,10	0.90
T28,27	0.90
Q10	0.10
Q24	0.10
Real power loss	4.2454
Voltage deviation	0.9090

Table4. *Performance of CPSO algorithm*

Iterations	35
Time taken (secs)	11.26
Real power loss	4.2454

Table5. *Comparison of results*

Techniques	Real power loss (MW)
SGA(Wu et al., 1998) [30]	4.98
PSO(Zhao et al., 2005) [31]	4.9262
LP(Mahadevan et al., 2010) [32]	5.988
EP(Mahadevan et al., 2010) [32]	4.963
CGA(Mahadevan et al., 2010) [32]	4.980
AGA(Mahadevan et al., 2010) [32]	4.926
CLPSO(Mahadevan et al., 2010) [32]	4.7208
HSA (Khazali et al., 2011) [33]	4.7624
BB-BC (Sakthivel et al., 2013) [34]	4.690
MCS(Tejaswini sharma et al.,2016) [35]	4.87231
Proposed CPSO	4.2454

CONCLUSION

In this paper a novel approach Customized Particle swarm optimization (CPSO) algorithm successfully solved optimal reactive power problem. Advance-and-retreat strategy has been used to bestow the clones with faster speed to find nearby local regions before subsequent clonal operation.The performance of the proposed algorithm has been tested in standard IEEE 30 bus test system.Simualtion results reveal about the better performance of the proposed algorithm in reducing the real power loss.

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