Selective Particle Swarm Optimization

Tamer M. Khalil, ***Member, IEEE*****, and Alexander V. Gorpinich,** ***Member, IEEE***

Abstract— **Using Particle Swarm Optimization (PSO) for solving nonlinear optimization problems has gained increasing attention in recent years. The method of Particle Swarm Optimization was introduced in 1995, then it adapted to search in binary space in 1997. Engineering optimization tasks often require optimization methods capable of select the values of the state variables from a set of available values (standard values). This work proposes a simple modification to the binary PSO to search in a selected space (selective PSO). The proposed method applied to a capacitor placement problem to select the optimal capacitor sizes from a set of available sizes.**

Keywords**—** Selective Particle Swarm Optimization and Capacitor Sizing

I. INTRODUCTION

The Particle Swarm Optimization method was first introduced by Kennedy and Eberhart [1] in 1995. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems [1]–[4]. One of reasons that PSO is attractive lies in very few parameters [5]. There are different versions of PSO that aim to widen its applicability. In [6] Kennedy and Eberhart proposed the first discrete version and Clerc [7] has shown promising results on variants of the PSO specialized for some constrained optimization problems such as TSP. Yoshida *et al.* [8] describe a modified version of the continuous PSO algorithm, which is able to handle both discrete and continuous variables, for reactive power and voltage control problems considering voltage security assessment. Eberhart and Shi [9] present a review on the developments and applications of particle swarm optimization technique.

In PSO algorithm, each member is called "particle", which represents a candidate solution to the problem at hand, and each particle flies around in the multi-dimensional search space with a velocity, which is constantly updated by the particle's own experience and the experience of the particle's neighbors. The basic PSO technique is the real valued PSO, whereby each dimension can take on any real valued number. On the other hand, in binary PSO each dimension of the particle can only take on the discrete values of 0 or 1.

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In most engineering applications optimization problems of continuous or discrete nature arise very often and the state variables maybe needed to be upgraded according to standard values. This paper presents a selective PSO for engineering optimization problems which deals with standard values such as capacitor sizes.

II. BASIC PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization is a stochastic optimization algorithm that simulates the social behaviors of bird flocking or fish schooling and the methods by which they find roosting places, foods sources or other suitable habitat. The PSO algorithm searches in parallel using a group of individuals.

In the basic PSO technique, suppose that the search space is d-dimensional,

- Each member is called *particle*, and each particle (*i-th particle*) is represented by d-dimensional vector and described as $X_i = [x_{i1},x_{i2},\ldots\ldots,x_{id}]$.
- The set of n particles in the swarm are called *population* and described as $pop = [X_1,X_2,\ldots.,X_n]$.
- The best previous position for each particle (the position giving the best fitness value) is called *particle best* and described as $PB_i = [pb_{i1}, pb_{i2}, \ldots.,pb_{id}]$.
- The best position among all of the particle best position achieved so far is called *global best* and described as $GB=[gb_1, gb_2, \ldots..,gb_d]$.
- The rate of position change for each particle is called *the particle velocity* and described as $V_i = [v_{i1}, v_{i2}\ldots v_{id}]$.
  At iteration k the velocity for d-dimension of i-particle is updated by:

$$v_{id}^{k+1} = w v_{id}^{k} + c_1 r_1 (pb_{id}^{k} - x_{id}^{k}) + c_2 r_2 (gb_{d}^{k} - x_{id}^{k}) \qquad (1)$$

Where $i= 1,2,\ldots,n$ and n is the size of population, w the inertia weight, c_1 and c_2 are the acceleration constants, and r_1 and r_2 are two random values in range[0,1].

The weighting function (w) is calculated using Eqn. (2) [2], [8]:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \qquad (2)$$

where w_{max} is an initial weight of value of 0.9, and w_{min} is the final weight of value 0.4. $iter_{max}$ is the maximum number of iterations. $iter$ is the current iteration number. c_1 and c_2 are set to 2.0.

- the i-particle position is updated by

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \quad (3)$$

III. SELECTIVE PARTICLE SWARM OPTIMIZATION (SPSO)

In 1997, Kennedy and Eberhart [6] have adapted the PSO to search in binary spaces, by applying a sigmoid transformation to the velocity component Eqn. (4) to squash the velocities into a range [0,1], and force the component values of the locations of particles to be 0's or 1's. The equation for updating positions Eqn.(3) is then replaced by Eqn. (5).

$$sigmoid(v_{id}^{k+1}) = \frac{1}{1+e^{-v_{id}^{k+1}}} \quad (4)$$

$$x_{id}^{k+1} = \begin{cases} 1, \text{ if } rand < sigmoid\left(v_{id}^{k+1}\right) \\ 0, \quad otherwise \end{cases} \quad (5)$$

In the selective PSO, the search space at each d-dimension $S_d = [s_{d1}, s_{d2}, ..., s_{dn}]$ is the set of d_n positions, where d_n is the number of the selected positions in the dimension d. As in the basic PSO, a fitness function F must be defined. In this case it maps at each d-dimension from d_n positions of the selective space S_d, where the position of each particle has been changed from being a point in real-valued space to be a point in the selective space. Therefore, the sigmoid transformation will be changed to Eqn. (6), and the *i-th* coordinate of each particle's position at a dimension d is a selective value, which updated by Eqn. (7)

$$sigmoid(v_{id}^{k+1}) = dn\frac{1}{1+e^{-v_{id}^{k+1}}} \quad (6)$$

$$x_{id}^{k+1} = \begin{cases} s_{d1} & if \quad sigmoid\ (v_{id}^{k+1}) < 1 \\ s_{d2} & if \quad sigmoid\ (v_{id}^{k+1}) < 2 \\ s_{d3} & if \quad sigmoid\ (v_{id}^{k+1}) < 3 \\ . & . \quad . \\ . & . \quad . \\ . & . \quad . \\ s_{dn} & if \quad sigmoid\ (v_{id}^{k+1}) \le dn \end{cases} \quad (7)$$

Where, $s_{d1}, s_{d2}, s_{d3}, ..., s_{dn}$ are the selected values in the dimension d.

Velocity values are restricted to some minimum and maximum values $[V_{min}, V_{max}]$ using Eqn. (8) [10].

$$v_{id}^{k+1} = \begin{cases} V_{max} & if \quad v_{id}^{k+1} > V_{max} \\ v_{id}^{k+1} & if \quad \left|v_{id}^{k+1}\right| \le V_{max} \\ V_{min} & if \quad v_{id}^{k+1} < V_{min} \end{cases} \quad (8)$$

To avoid invariability of the velocity value of the particle i at the dimension d at the maximum or the minimum values and to avoid the oscillation of the velocity value of the particle i at the dimension d between the maximum and the minimum values we use Eqn. (9) to force each particle to go through the search space.

$$v_{id}^{k+1} = \begin{cases} rand * v_{id}^{k+1} & if \quad Iv_{id}^{k+1}I = Iv_{id}^{k}I \\ v_{id}^{k+1} & \quad otherwise \end{cases} \quad (9)$$

As a simple illustrative example, fined the values of the state variables X and Y to give the minimum value of the fitness function F,

$F= (X-15)^2 + (Y- 23)^2$.

Where, X={0, 3, 7, 8, 13, 19, 22, 25, 28} and Y={1, 3, 6, 15, 19, 24, 28}.

- This example is 2 dimensions (*X, Y*).
- The number of the selected values in dimension X, $x_n = 9$.
- The number of the selected values in dimension Y, $y_n = 7$.
- The minimum value of F will be 5, when $X= s_{X5} =13$ *and* $Y= s_{y6} =24$.

The PSO technique can be expressed as follow:

Step 1: *(Initialization):* Set the iteration number $k=0$. Put the initial value of each dimension of each particle to random value from the selective space, $\{X^0_i, i=1,2,....,n\}$, where $X^0_i=[x^0_{i1},x^0_{i2},.....,x^0_{id}]$, and Generate randomly their initial velocities $V^0_i=[v^0_{i1}, v^0_{i2},....., v^0_{id}]$. Evaluate the objective function for each particle $f(X^0_i)$. If the constraints are satisfied, then set the *particle best* $PB^0_i=X^0_i$, and set the *particle best* which give the best objective function among all the particle bests to *global best* GB^0. Else, repeat the initialization.

Step 2: *Update iteration counter* $k=k+1$

Step 3: *Update velocity* using Eqns. (1, 8 and 9).

Step 4: *Update the sigmoid function* using Eqn. (6)

Step 5: *Update position* using Eqns. (7).

Step 6: *Update particle best:*

If $f_i\left(X_i^k\right) < f_i\left(PB_i^{k-1}\right)$ then $PB_i^k = X_i^k$

else $PB_i^k = PB_i^{k-1}$

Step 7: *Update global best:* $f\left(GB^k\right) = \min\left\{f_i\left(PB_i^k\right)\right\}$

If $f\left(GB^k\right) < f\left(GB^{k-1}\right)$ then $GB^k = GB^k$

else $GB^k = GB^{k-1}$

Step 8: Stopping criterion: If the number of iteration exceeds the maximum number iteration, then stop, otherwise go to step 2.

IV. USING THE SELECTIVE PSO FOR OPTIMAL PLACEMENT AND SIZING OF CAPACITOR BANKS

The general capacitor problem is defined as a problem of finding the optimal locations and sizes of capacitor banks, such that the cost of peak power loss, energy loss and the cost of capacitors are minimized, and operational constraints satisfied under different load conditions. Therefore, there exist a finite number of standard capacitor sizes, each of which is an integral multiple of the smallest size. In addition, the cost per kvar varies from one size to another.

In order to apply the selective PSO to the capacitor placement problem, we should define the fitness function, the operational constraints, the dimensions and the selective space.

- The fitness function is to minimize the total cost of power loss, energy loss and capacitors (or maximize the net saving).
- The operational constraints are the voltage limits, and the maximum allowable capacitors sizes.
- The dimensions will be the candidate buses to place the capacitors at it.
- The selective space at each dimension will be the available capacitor sizes plus one which indicate that there are no capacitors at this dimension (this bus).

Illustrative Example:

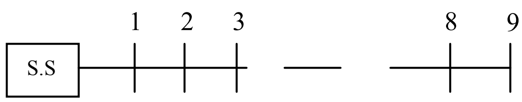

Fig. 1: Nine-bus test feeder

The 9-bus radial distribution feeder was taken as test feeder in [11] and shown in Fig. 1. This test feeder has been solved in [11] using different methods which based on fuzzy logic and heuristic strategy and finally they use the exact solution.

To demonstrate the effectiveness of the selective PSO in solving the capacitor placement and sizing problems, this problem will be solved in two cases:

1. It is desired to find the optimal values of capacitor sizes to be placed at the same buses used in [11] (Method 3, Method 5 and Exact solution).
2. It is desired to find the optimal placement and sizing of capacitors (apply the selective PSO to all the 9-buses).

The fitness function is to minimize the total annual cost due to power losses and capacitor placement. The maximum allowable capacitor size is 4050 kvar. The available capacitor sizes and its annual costs are shown in Table 1.

TABLE 1
YEARLY COST OF FIXED CAPACITORS [11]

	1	2	3	4	5	6	7
Capacitor size (kvar)	150	300	450	600	750	900	1050
Capacitor cost ($/kvar)	0.5	0.35	0.253	0.22	0.276	0.183	0.228
	8	9	10	11	12	13	14
Capacitor size (kvar)	1200	1350	1500	1650	1800	1950	2100
Capacitor cost ($/kvar)	0.17	0.207	0.201	0.193	0.187	0.211	0.176
	15	16	17	18	19	20	21
Capacitor size (kvar)	2250	2400	2550	2700	2850	3000	3150
Capacitor cost ($/kvar)	0.197	0.17	0.189	0.187	0.183	0.18	0.195
	22	23	24	25	26	27	
Capacitor size (kvar)	3300	3450	3600	3750	3900	4050	
Capacitor cost ($/kvar)	0.174	0.188	0.17	0.183	0.182	0.179	

In these cases:

- The selective space at each dimension represented by: $S_d = [0, 150, 300, 450, \ldots\ldots, 4050]$

In Case 1 Method 3

- The example is 4 dimensions (represents the candidate buses {2, 3, 5, 9}).
- The number of the selected position at each dimension will be: $2_n = 3_n = 5_n = 9_n = 28$ (27 size + the probability of no capacitor).

In the same way Case 1 Method 5 is 4 dimensions {3, 4, 5, 9} and Case 1 Exact solution is 4 dimensions {2, 4, 5, 9}.In Case 2 the example is 9 dimensions (represents all the buses).

The simulation results showed in Table 2 clear that:

The optimization of the system using the selective PSO indicate yearly benefits better than that indicated by the methods used in [11] at the same candidate buses.

The optimal placement and sizing (apply the algorithm to all the 9 buses) using the selective PSO indicates the best benefits.

TABLE 2
SIMULTION RESULTS FOR THE ILLUSTRATIVE EXAMPLE

Bus number	before capacitor placement	Case 1						Case 2
		Method 3 [11]	Selective PSO	Method 5 [11]	Selective PSO	Exact Solution [11]	Selective PSO	Selective PSO
1	---	---	---	---	---	---	---	150
2	---	3300	3450	---	---	3600	3900	3000
3	---	3900	3450	2850	3750	---	---	3450
4	---	---	---	2100	2250	4050	3900	1800
5	---	1200	2100	1050	1350	1650	1650	0
6	---	---	---	---	---	---	---	750
7	---	---	---	---	---	---	---	150
8	---	---	---	---	---	600	600	0
9	---	900	600	900	600	---	---	600
Min. voltage[pu]	0.838	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Max. voltage[pu]	0.994	1	1	1	1	1	1	1
Power losses [kW]	783.8	689	682.8	692	689.65	686.4	684.78	680.36
Capacitor cost [$/year]	---	1652.7	1798.8	1295.3	1541	1787.7	1870.1	2014.2
Total cost [$/year]	131675	117345	116511	117495	117402	117109	116913	116314
Benefits [$/year]	**---**	**14330**	**15164**	**14180**	**14273**	**14566**	**14762**	**15361**

V. CONCLUSION

A simple modification to the binary PSO to search in a selected space is proposed in this paper. In the basic PSO the search space is a real-valued space where in the binary PSO search space is a set of 0^s and 1^s, but in the selective PSO the search space is a set of selected values. The main advantage of this algorithm is its simplicity. The selective PSO is suited to the optimization problems which deal with the standard values such as capacitor sizes.

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REFERENCES

[1] J. Kennedy and R. Eberhart, "Particle swarm optimization," *in Proc .IEEE Int. Conf. Neural Networks*, vol. IV, Perth, ustralia, 1995, pp. 1942–1948.

[2] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in *Proc IEEE Int. Conf. Evol. Comput.*, Anchorage, AK, May 1998, pp. 69–73.

[3] Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," in *Proc. IEEE Int. Conf. Evol. Comput.*, Washington, DC, July 1999, pp. 1945–1950.

[4] R. C. Eberhart and Y. Shi, "Comparison between genetic algorithms and particle swarm optimization," in *Proc. IEEE Int. Conf. Evol. Comput.*, Anchorage, AK, May 1998, pp. 611–616.

[5] Y. Shi and R. Eberhart, "Parameter selection in particle swarm optimization," *in Proc. 7th Ann. Conf. Evolutionary Program.*, Mar. 1998, pp. 591–600.

[6] J. Kennedy and R. C. Eberhart, "A Discrete Binary Version of the Particle Swarm Algorithm," *Proc. of the conference on Systems*, Man, and Cybernetics SMC97, pp.4104-4109, 1997.

[7] M. Clerc, "The Swarm and the Queen: Towards a Deterministic and Adaptive Particle Swarm Optimization," *Proc. Congress on Evolutionary Computation*, Washington, DC, 1999.

[8] H. Yoshida, K. Kawata, Y.Fukuyama, S.Takayama, and Y. Nakanishi "A particle swarm optimization for reactive power and voltage control considering voltage security assessment" *IEEE Trans. Power Delivery*, vol. 15, pp.1232-1239, Nov.2000.

[9] R. C. Eberhart and Y. Shi, "Particle swarm optimization: developments, applications, resources." *Proc. of Congress on Evolutionary Computation*, 2001, pp.81-86.

[10] Tasgetiren. M. F. Liang Y. C.. "A Binary Particle Swarm Optimization Algorithm for Lot Sizing Problem". *Journal of Economic and Social search*. Vol.5 No.2. pp. 1-20. 2003.

[11] S. F. Mekhamer, S. A. Soliman, M. A. Moustafa, and M. E. El-Hawary, "Application of Fuzzy Logic for Reactive-Power Compensation of Radial Distribution Feeders," *IEEE Trans. Power Systems,* vol. 18, no. 1, pp. 206–213, Feb. 2003.

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