Particle Swarm Optimization Algorithm for the Solution of Nonconvex Economic Dispatch Problem with Valve Point Effect

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Abstract

In this study, particle swarm optimization (*PSO*) algorithm has been used for the solution of the economic dispatch problem with valve point effect. In these kind of problems, fuel cost curve increases as sinusoidal oscillations. In the solution of the problem B loss matrix has been used for the calculation of the transmission line losses. Total fuel cost rate has been minimized under electrical constraints. *PSO* algorithm has been applied to three different test systems one with 6 buses 3 generators, the other with 14 buses 5 generators (*IEEE*) and the last one with 30 buses 6 generators (*IEEE*). The obtained optimum solution values have been compared with optimum solution values obtained by the application of different methods in literature and the results of them have been discussed.

1. Introduction

Nowadays due to the increasing need of cheap energy in every field of life, economic power dispatch problem has become one of the most significant issues in the operation of power systems. Economic power dispatch problem is known as the meeting of the present load in the system by the generation units under the limits of the system with minimum fuel cost rate [1-11].

Generally, when the valve point effects are ignored, fuel cost function for each generation unit is approximately shown with a quadratic function. This approximate calculation causes to find a faulty optimum solution. If various types of physical and operational constraints are added into the problem for correction of the optimal solution, the problem turns into a nonlinear constrained optimization problem. Economic dispatch problem with valve point effect is one of these problems. Economic dispatch problem with valve point effect is a nonconvex problem and it is hard to find an optimal solution for this problem [1-10].

In the system formed of thermal generation units with multi-valve steam stands, fuel cost function is represented with a nonconvex function. The fuel cost function used for these kinds of generation units includes sinusoid oscillations [1-10].

In literature, nonconvex economic dispatch problems have been solved by a new hybrid search algorithm and genetic algorithm [1], big bang - big crunch optimization algorithm [2], a partition approach algorithm [3], anti-predatory particle swarm optimization or a developed anti-predatory particle swarm optimization [4,5], a differential evolution algorithm or a developed differential evolution algorithm [6-10].

In this study, particle swarm optimization (PSO) algorithm has been used in the solution of valve-point effect nonconvex economic dispatch problem. PSO can be coded simply and is a strong algorithm.

2. Problem Formulation

The solution of the economic power dispatch problem is found by the minimization of total fuel cost rate under the limits of the system. And this is the object function of the optimization problem [1-10,12-14].

$$\min F_{total} = \min \sum_{n=1}^{N} F_n(P_{G,n}) \quad (1)$$

The fuel cost function of the generation units has been shown in Figure 1. In the figure the graphic convex shown by broken line is fuel cost function and as represented in equation (2) has been taken as quadratic function for each unit [10,12-14].

$$F_n(P_{G,n}) = a_n + b_n P_{G,n} + c_n P_{G,n}^2 , \quad (R/h) \quad (2)$$

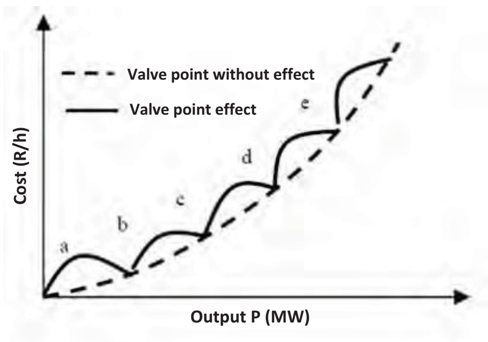

Figure 1. The input-output characteristic of valve point effect generation unit

In fact, the input-output curve of multi-valve steam stand generation units is very different when it is compared with the equality in equation (2). The inclusion of the valve point effect in the fuel cost of the generation unit makes the representation of the fuel cost more convenient. As the valve point is finalized with surges, the fuel cost function includes higher nonlinear series. For this reason, as for the study aimed at considering the valve point effects, a nonconvex function is used in the equation (3) that varied as in Figure 1. [1-10].

$$F_n(P_{G,n}) = a_n + b_n P_{G,n} + c_n P_{G,n}^2 + \left| e_n.\sin(f_n(P_{G,n}^{\min} - P_{G,n})) \right| , \quad (R/h) \tag{3}$$

In this equation, $F_n(P_{G,n})$ represents fuel cost function of the *n*-th generation unit as R/h, a_n, b_n, c_n, e_n and f_n symbolize the coefficients of the fuel cost function in the *n*-th generation unit, respectively, $P_{G,n}$, represents the output power of the *n*-th generation unit in MW. e_n and f_n are coefficients that represent the valve point effect.

The power balance constraint in lossy system has been taken as in equation (4).

$$P_{load} - P_{loss} - \sum_{n=1}^{N} P_{G,n} = 0 \tag{4}$$

The generating capacity constraints are given as below.

$$P_{G,n}^{\min} \le P_{G,n} \le P_{G,n}^{\max} , \; (n \in N) \tag{5}$$

Power losses, which occur in dispatch lines of the system, are calculated through *B* loss matrix by using the following equation [11-14].

$$P_{loss} = \sum_{n=1}^{N}\sum_{j=1}^{N} P_{G,n}.B_{nj}.P_{G,j} + \sum_{n=1}^{N} B_{0n}.P_{G,n} + B_{00} \tag{6}$$

3. Particle Swarm Optimization (PSO) Algorithm

PSO has been introduced as a new intuitional method by Kennedy and Eberhart in 1995. The method has been developed by observing the social behavior of bird flocks and fish schools. PSO algorithm is a global optimization algorithm to obtain objective function change with no need to use mathematical procedures. The first original version of the method could only be used for the solution of nonlinear continuous optimization problems. Then, the method has been improved to enable its use in the global optimal solutions of more complex engineering problems. A flock or school in the algorithm is composed of many particles, and each particle represents a potential solution [7-9,11,12,15,16].

Bird flocks or fish schools search a specific area to be able to find food or shelter. PSO algorithm is formed by social behavior of these flocks. The first of these behaviors is the tendency of each particle to take the best position from their past memories. The second behavior is the movement made to follow the particle which is the nearest to the food. The last behavior is the past speed value which enables the wide area search. These behaviors form the basis for PSO algorithm [11,16].

Although PSO appears to be a simple and effective optimization tool as it can catch global optimum values very fast without distracted by local optimum values, and can be coded easily, it also has some weak points. For example; it depends on initial conditions, and some time is needed for more effective combination of different parameters for consistency [8-9,11,12,15,16].

Particles are initially produced randomly to spread out in the feasible search space. The particle has its own position and flight velocity. Particles keep these values unchanged for each iteration throughout the optimization process. Equations are updated to determine the location of each particle for the next iteration. Particles move towards the optimal solution at each iteration [7-9,11,12,15,16].

Each particle initially is located randomly in PSO algorithm. New velocity of each particle is determined by equation (7) and new position is determined by equation (8).

$$\begin{aligned} v_i(k+1) = w.\, v_i(k) + c_1.r_1(k).(Xlbest_i(k) - x_i(k)) \\ + c_2 r_2(k)(Xgbest(k) - x_i(k)) \end{aligned} \tag{7}$$

$$x_i(k+1) = x_i(k) + v_i(k+1) , \; v_i(0)=0 \tag{8}$$

In equations, k represents iteration number, M particle numbers in each iteration (swarm population), $x_i(k)$, $i \in (1,\ldots,M)$ location of *i*-th particle in *k*-th iteration, $v_i(k)$, $i \in (1,\ldots,M)$ velocity of *i-th* particle in *k-th* iteration, positive numbers c_1 and c_2 represents learning factors (cognitive and social acceleration constants), $r_1(k), r_2(k) \sim U(0,1)$ random number regularly distributed between *0* and *1*, and w represents inertia weight factor. The best location memory of each particle in the population is recorded in $Xlbest_i(k)$ variable. Also, the location of the particles in the swarm which is the closest to the optimum is saved in $Xgbest(k)$ [7-9,11,12,15,16].

Linearly decreased inertia weight factor, w, is a variable which regulates previous velocity value, and calculated by the equation (9).

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \tag{9}$$

where $w_{\min}$ and $w_{\max}$ represent the initial and final inertia weight factors respectively, $iter$ is current iteration number, and $iter_{\max}$ is the maximum iteration number in the equation [7-9,11,12,15,16].

The flowchart of the PSO algorithm is given in Figure 2.

4. The Application of Particle Swarm Optimization to the Problem

In this section, the application of *PSO* algorithm to the valve point effect nonconvex economic power dispatch problem has been explained.

Firstly, swarm elements (namely the particles) are formed randomly. $P_{G,n}$, $n \in N_G$ values are assigned randomly for *M* particle by using the following equation [1, 11, 17].

$$P_{G,n} = P_{G,n}^{\min} + U(0,1) \times (P_{G,n}^{\max} - P_{G,n}^{\min}) \tag{10}$$

In equation (4), it is important to form the particle in order to provide the given active power equality limit. Therefore, *l*-th generator power $P_{G,l}$ is selected randomly. The value of $P_{G,l}^{old}$ is taken as $P_{loss}^{old} = P_{loss}^{start} = 0$ at the beginning and calculated from equation (11).

$$P_{G,l}^{old} = P_{load} + P_{loss}^{old} - \sum_{n \in N_G, l \notin N_G} P_{G,n} \qquad (11)$$

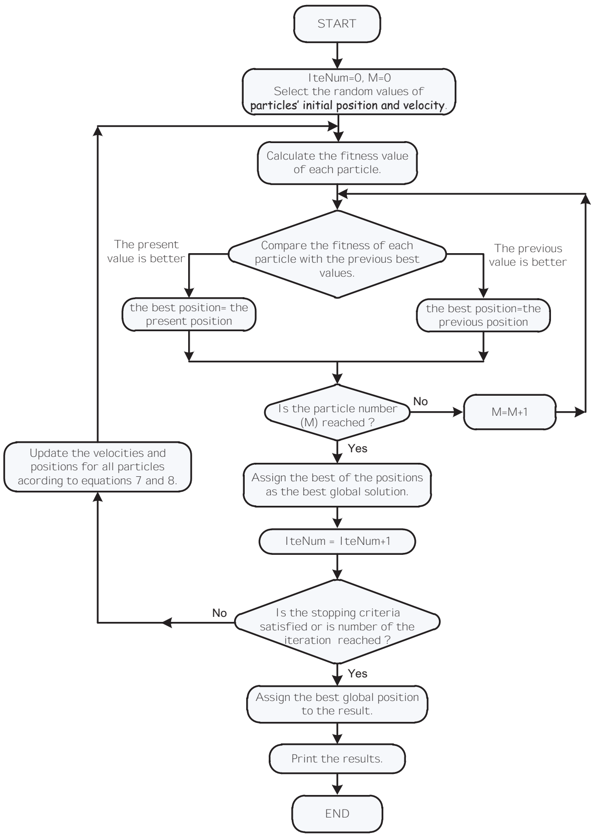

Figure 2. The PSO algorithm flowchart

$P_{G,l}^{new}$ is calculated from equation (6) after finding $P_{G,l}^{old}$. According to this, the value of $P_{G,l}^{old}$ is calculated from the following equation again.

$$P_{G,l}^{new} = P_{G,l}^{old} + P_{loss}^{new} - P_{loss}^{old} \qquad (12)$$

At the end of this process, the error value (ε) is checked from equation (13) and when ε is under the value of TOL_{ε}, the equality in equation (4) is also provided.

$$\varepsilon = \left| P_{loss}^{new} - P_{loss}^{old} \right|, \quad \varepsilon \le TOL_{\varepsilon} \qquad (13)$$

In this case, it is checked whether the obtained $P_{G,l}^{new}$ value provides the equation (5) limit or not. If it does so, by using these solution values suggested by the particle the value of the object function is calculated from equation (1) and the process is carried on. If it does not provide, we turn to equation (10) and repeat the random assignment process. In this study, the object function in equation (1) has been defined as fitness function. In this way since the particle produced by the present process includes a solution, it is added to the swarm. This process continues until the *M* particle (swarm population) is completed.

The particle with the best fitness value of the particles in $Xgbest(k)$ is selected for each iteration. When the iteration process is completed, the solution with the most fitness function value is selected as the best solution.

Maximum iteration number is defined as stopping criterion. When this number is reached, the iteration is stopped.

5. Sample Problem Solutions

PSO is applied to 6-bus 3-generator test system for *210 MW*, 14-bus 5-generator (IEEE) test system for *259 MW* and 30- bus 6-generator (IEEE) test system for *283.4 MW* load demand separately. The cost function coefficients in equation (3), operation limit values in equation (5), B loss matrix values in equation (6) have been taken from literature [1].

In this study, the values of PSO parameters have been taken as the following; particle number (M) *25*, gen number (N) *5*, $w_{\max} = 0.9$, $w_{\min} = 0.4$, $c_1 = c_2 = 2.05$, iteration number *100*, also error toleration in equation (13) $TOL_{\varepsilon} = 1 \times 10^{-6}\,MW$.

The optimum results obtained from the solution of the test systems have been given respectively as for 6-bus system in Table 1, for 14-bus test system in Table 2 and for 30-bus test system in Table 3 together with the results in literature [1].

Table 1. The results obtained for 6-bus test system
($P_{load} = 210\ MW$)

Bus No	*GA [1]*	*NSOA [1]*	*DE [10]*	*PSO*
$P_{G,1}(MW)$	53.2604	50.0000	50.0000	***50.4739***
$P_{G,2}(MW)$	88.9645	86.0678	74.6523	***74.1958***
$P_{G,3}(MW)$	74.7693	79.7119	90.8627	***90.8627***
$\sum P_{G,n}\ (MW)$	216.9942	215.7797	215.5150	***215.5324***
$F_{total}\ (R/h)$	3252.4576	3205.9905	*3187.8911*	***3189.820***
$P_{loss}(MW)$	6.9939	5.7797	5.5515	***5.5324***
Time (s)	1.0310	0.0140	0.6904	***0.3117***

Table 2. The results obtained for 14-bus test system
($P_{load} = 259\ MW$)

Bus No	*GA [1]*	*NSOA [1]*	*DE [10]*	*PSO*
$P_{G,1}(MW)$	172.7647	181.1287	199.2997	***197.4696***
$P_{G,2}(MW)$	26.6212	46.7567	20.0000	***20.0000***
$P_{G,3}(MW)$	24.8322	19.1526	20.9997	***21.3421***
$P_{G,6}(MW)$	23.4152	10.1879	15.4322	***11.6762***
$P_{G,8}(MW)$	19.1885	10.7719	12.5216	***17.7744***
$\sum P_{G,n}\ (MW)$	266.8217	267.9977	268.5532	***268.2623***
$F_{total}\ (R/h)$	926.5530	905.5437	834.1302	***836.4568***
$P_{loss}(MW)$	7.8250	8.9977	9.5532	***9.2623***
Time (s)	0.3910	0.0150	0.6706	***0.3484***

Table 3. The results obtained for 30-bus test system (P_{load} = *283.4 MW*)

Bus No	*GA [1]*	*NSOA [1]*	*DE [10]*	*PSO*
$P_{G,1}(MW)$	150.7244	182.4784	149.7320	**197.8648**
$P_{G,2}(MW)$	60.8707	48.3525	52.0565	**50.3374**
$P_{G,5}(MW)$	30.8965	19.8553	26.2277	**15.0000**
$P_{G,8}(MW)$	14.2138	17.1370	24.1582	**10.0000**
$P_{G,11}(MW)$	19.4888	13.6677	23.5726	**10.0000**
$P_{G,13}(MW)$	15.9154	12.3487	16.9955	**12.0000**
$\sum P_{G,n}$ (MW)	292.1096	293.8395	292.7425	**295.2022**
F_{total} (R/h)	996.0369	984.9365	963.0010	**925.7581**
$P_{loss}(MW)$	8.7060	10.4395	9.3425	**11.8022**
Time (s)	0.5780	0.0150	0.6558	**0.3529**

The graphics showing the total fuel cost values obtained from the application of PSO to the test systems and also showing the variations of the power generation values according to the iterations have been given respectively for 6-bus system in Figure 3 and 4, for 14-bus system in Figure 5 and 6, for 30-bus system in Figure 7 and 8.

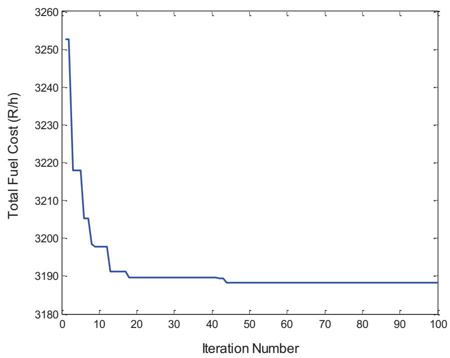

Figure 3. The variation in total fuel cost rate according to the iteration number (*6-bus system*)

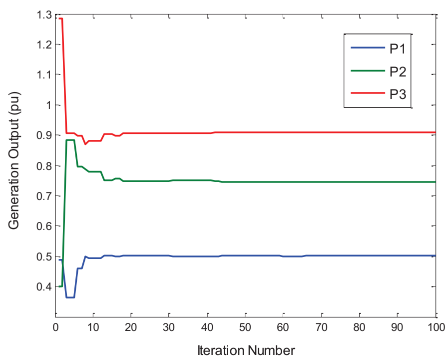

Figure 4. The variations of the power generation values (*6-bus system*)

The change in the fuel cost of 6-bus test system is seen not to have changed after 55-*th* iteration in Figure 3. In Figure 4, the output power values of the generation units almost do not change approximately after 55-*th* iteration. In this case, it can be said that the solution for 6-bus test system has converged to the optimum solution after 55-*th* iteration.

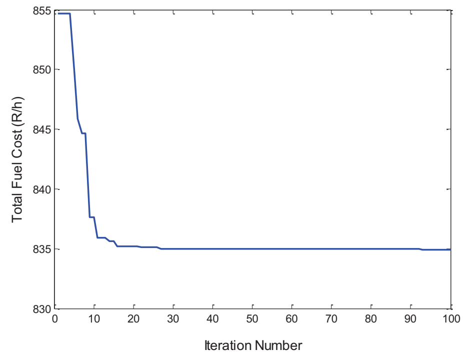

Figure 5. The variation in total fuel cost rate according to the iteration number (*14-bus system*)

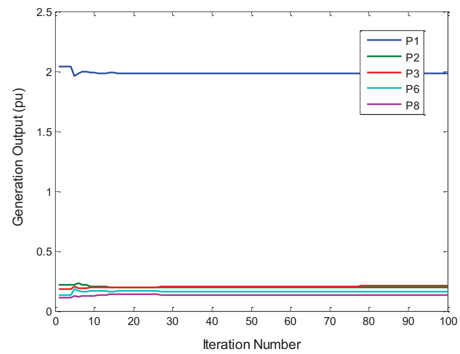

Figure 6. The variations of the power generation values according to the iteration number (*14-bus system*)

The change in the fuel cost of 14-bus test system is seen to have been very little after 28-*th* iteration in Figure 5. In Figure 6, the output power values of the generation units almost do not change after 28-*th* iteration. In this case, it can be said that the solution for 14-bus test system has converged to the optimum solution after 28-*th* iteration.

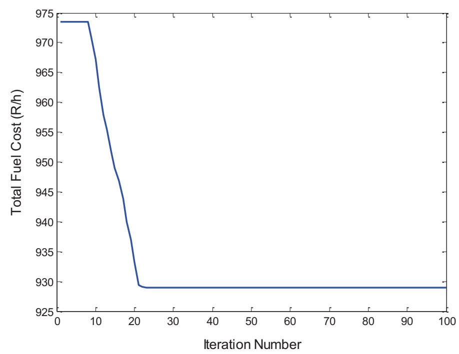

Figure 7. The variation of the power generation values in total fuel cost rate according to the iteration number (*30-bus system*)

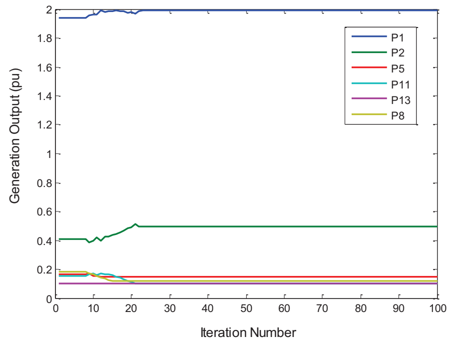

Figure 8. The variations of the power generation values (*30-bus system*)

In Figure 7, no change has happened in the fuel cost of 30-bus test system after 22-*th* iteration. In Figure 8, the output power values of the generation units almost do not change after 22-*th* iteration. In this case, it can be expressed that the solution for this test system has converged to the optimum solution after 22-*th* iteration.

When Table 1, 2 and 3 are analyzed and the obtained results are compared with the results in literature [1] and [10], it has been seen that the results obtained by PSO are better than the results obtained by genetic algorithm (GA) and hybrid search (NSOA) method and have converged the results obtained by (DE).

6. Conclusion

In this study, PSO has been applied to the 6, 14, and 30-bus test systems of IEEE for the solution of valve point effect nonconvex economic power dispatch problem.

As a result PSO, which catches the global optimum in a very fast way without hanging on local optimums, is a very simple algorithm and can be coded easily. If it is compared with genetic algorithm; the advantage of PSO is that it can be performed very easily and it has very few parameters that must be fixed PSO has been applied in many fields successfully. It has been shown that with these qualities of it, PSO can also be easily applied for the solution of valve point effect nonconvex economic power dispatch problem.

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