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An Efficient Algorithm for Economic Load Dispatch Considering Valve Point Loading Effect

Anita Sahni, Krishna Teerth Chaturvedi

Abstract: ***A simple and efficient algorithm is proposed for solving the economic dispatch problem of power system with valve point discontinuities employing a particle swarm optimization based approach. Evolutionary methods such as GA and PSO are known to perform better than conventional gradient based optimization methods for non convex optimization problems. This reactive power management in economic load dispatches plays a vital role in improving power quality of the system. The power compensation and economic load dispatches is major problem in distribution network. The power is maintain the state of the UPQC (Unified power quality conditioner). The UPAC controlled by the STATCOM or DSTATCOM. The performance of the proposed method has been compared with conventional PSO. The effectiveness of the algorithm has been tested on a test system having three generating units.***

Keywords: ***UPQC, MOPSO, STATCOM, DSTATCOM Power, Reactive, Economic load dispatch (ELD), Power system optimization, Particle swarm optimization (PSO).***

I. INTRODUCTION

Power systems are large and complex electrical networks. In any power system, generations are located at few selected points and loads are distributed throughout the network. In between generations and loads, there exist transmission and distribution systems. In the power system, the system load keeps changing from time to time as shown.

Power system characteristics:

- It must gracefully control, for all intents and purposes wherever the client requests.
- It must gracefully capacity to the clients consistently.
- It must have the option to gracefully the regularly changing burden request at untouched.
- The power provided ought to be of acceptable quality.
- The power provided ought to be prudent.
- It must fulfill fundamental security necessities.

Economic dispatch is one of the main functions of modern energy management system. It is formulated as an optimization problem with the objective of minimizing the total fuel cost while satisfying the specified constraints.

Conventionally, input-output characteristics of generators, known as cost functions, are approximated using quadratic or piecewise quadratic functions, assuming that the incremental cost curves of generators are monotonically increasing [1].

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* Correspondence Author
Anita Sahni*, Research Scholar, Department of Electrical and Electronics Engineering, RGPV University Bhopal (M.P), India.
Dr. K. T. Chaturvedi, Assistant Professor, Department of Electrical and Electronics Engineering, RGPV University Bhopal (M.P), India.

However, in practice, this assumption is not valid because the cost functions exhibit higher order non-linearities and discontinuities due to valve point loading effects in units fired by fossil fuels [2]. The cost function needs to be more realistically expressed as a piecewise non-linear function rather than a single quadratic function [3]. The ELD problem with valve point effects is denoted as a non smooth optimization problem having complex and non convex characteristics which make the challenge of obtaining the global minima, very difficult [4]. Therefore, conventional gradient based optimization methods fail in such cases and result in inaccurate dispatches [5]. A classical approach to solve the ELD problem with valve point loading is dynamic programming in which all possible solutions are enumerated while choosing for a optimal dispatch [6]. This method suffers from the problem of dimensionality and excessive evaluation at each stage [7]. Genetic algorithms are effective search tools based on the mechanics of natural selection and survival of the fittest found in natural genetics [8]. They merge solution evaluation with randomized structured exchange of information between various solutions to obtain optimality [9]. GAs are robust tools as no restriction is imposed on search space during the process of evaluation [10]. The driving force behind these algorithms is their ability to exploit historical information from previous solutions to improve the performance of future solutions. GAs maintain a population of solutions throughout evaluation, therefore they are not limited by initial single point guesses. The PSO is a flexible, robust population based stochastic search/optimization algorithm with inherent parallelism [11]. Unlike conventional techniques, PSO can handle non-differentiable objective functions easily. This method is less likely to get trapped in local minima unlike GA. In a PSO, the search for optimal solution is conducted using a population of particles, each of which represents a possible solution to the optimization problem [12]. Particles fly around in a multi dimensional search space by adjusting its trajectory towards its own previous best and the best of its neighbors. The PSO technique is capable of generating high quality solutions with stable convergence characteristics. It is increasingly gaining acceptance for solving various power system problems. The paper presents a PSO based approach for solving the ELD problem with non smooth cost functions.

II. PARTICLE SWARM OPTIMIZATION

A PSO is a multi agent search technique that traces its evolution to the emergent motion of a flock of birds searching for food. It is a simple and powerful optimization tool which scatters random particles into the problem space.

These particles, called swarms collect information from each other through an array constructed by their respective positions.

The particles update their positions by comparing their relative convergence towards the global optimum. The update mode is termed as the velocity of particles. Position and velocity are both updated in a heuristic manner through random generation. The success of global best depends here on the neighborhood of a particle. Treating all particles as neighbors does produce good results as such a vast neighborhood often results in inferior solutions. Using smaller, overlapping neighborhood has been found to be more effective. Particle swarm optimization (PSO) is one of the evolutionary computation techniques. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous linear and nonlinear optimization problems. The PSO technique can generate high-quality solutions within shorter calculation time and have more stable convergence characteristic than other stochastic methods. It has been found that the PSO quickly finds the high-quality optimal solution for many power system optimization problems.

III. PSO BASED ELD SOLUTION WITH VALVE POINT LOADING

This paper presents a quick solution to the economic dispatch problem with valve point loading, using the PSO algorithm.

To solve the standard economic dispatch problem, consider the operation of a power system with N units, each loaded to P_i, to satisfy a total load demand P_D including total transmission losses P_L. Let the fuel input-power output cost function of each unit be represented by a function F_i. The units are to be loaded so that the total fuel cost, F_T for the N number of generating units is minimized subject to the power balance and unit upper and lower operating limits:

$$\min \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

subject to:

$$\sum_{i=1}^{N} P_i - (P_D + P_L) = 0$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1,2,\ldots,N \tag{2}$$

For a given real load P_D at all the buses, the system loss P_L is a function of active power generation at each generating unit. To calculate system losses, two methods are in general use. One is the method of penalty factors and the other is the use of constant loss formula coefficients or B-coefficients. The latter is commonly used by the power utilities and is adopted in this study. In this method, transmission losses are expressed as a quadratic function of generations:

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j \tag{3}$$

The fuel – cost function without valve-point loadings of the generating units is given by

$$F(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{4}$$

The fuel – cost function considering valve – point loadings of the generating units is given by [4] as

$$F(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \times \sin\left(f_i \times \left(P_{i\min} - P_i\right)\right)\right| \tag{5}$$

where a_i, b_i and c_i are the fuel-cost coefficients of the i^{th} unit, and c_i and f_i are the fuel cost-coefficients of the i^{th} unit with valve-point effects.

The generating units with multi valve steam turbines exhibit a greater variation in the fuel-cost functions. The valve-point effects introduce ripples in the heat-rate curves.

Let x and v denote a particle coordinates (position) and its corresponding flight speed (velocity) in a search space, respectively. The best previous position of a particle is recorded and represented as $pbest$. The index of the best particle among all the particles in the group is represented as $gbest$. Each particle knows the best value so far $(pbest)$ and the best value in the group $(gbest)$. The particle tries to modify its position using the current velocity and the distance from $pbest$ and $gbest$. At last, the modified velocity and position of each particle can be calculated as using the following formulas:

$$v_i^{k+1} = w * v_i^k + c_1 * rand_1 * (pbest_i - x_i) + c_2 * rand_2 * (gbest_i - x_i) \tag{6}$$

$$x_i^{k+1} = x_i + v_i^{k+1} \tag{7}$$

where

v_i^k : velocity of particle i at iteration k

w : inertia weight parameter

c_1, c_2 : learning factors

$rand_1, rand_2$: random number between 0 and 1

x_i^k : position of particle i at iteration k

The role of inertia weight w is very important for the convergence of PSO algorithm. The inertia weight is used for controlling the effect of the previous velocities on the current velocity. Therefore, this parameter regulates the trade off between the global and local exploration capabilities of the particle. A large inertia weight helps in good global search, while a smaller value facilitates local exploration. Therefore, the practice is to use larger inertia weight factor during initial exploration and gradual reduction of its value as the search proceeds in further iterations. In general, the inertia weight w is set according to the following equation:

$$w = w_{\max} - \left(\left(w_{\max} - w_{\min}\right) * iter / iter_{\max}\right) \tag{8}$$

where

$iter$: current iteration number

$iter_{max}$: maximum number of iterations.

Usually, the value of w is varied between 0.9 and 0.4. Constant c_1 pulls the particles towards local best position whereas c_2 pulls it towards the global best position. Usually these parameters are selected in the range of 0 to 4.

In the iteration process velocity is limited by some maximum value v_i^{max}. The parameter v_i^{max} determines the resolution, or fitness with which regions are to be searched between the present position and the target position. This limit enhances the local exploration of the problem space. If v_i^{max} is too high, particles might fly past good solutions. If v_i^{max} is too small, particles may not explore sufficiently beyond local solutions. In many experiences with PSO, v_i^{max} was often set at 10%-20% of the dynamic range of the variable on each dimension.

The PSO method has been used to find out the optimal generation allocation when the generation cost curves are non smooth. Its implementation consists of the following steps:

Step (1) In the ELD problem the number of on-line generating units is the 'dimension' of this problem. The particles are randomly generated between the maximum and the minimum operating limits of the generators. For example, if there are N units, the i^{th} particle is represented as follows:

$$P_i = (P_{i1}, P_{i2}, P_{i3}.................P_{iN}) \tag{9}$$

These initial particles must be feasible solutions of the problem satisfying the practical operating constraints specified by (2).

Step (2) The particle velocities are generated randomly in the range $[[-V_j^{max}, V_j^{max}]$.

The maximum velocity limit for the j^{th} generating unit is computed as follows:

$$V_j^{max} = \frac{P_{j.max} - P_{j\,min}}{R} \tag{10}$$

Where R is the chosen number of intervals in the j^{th} dimension. For all the examples tested using the PSO approach, V_j^{max} was set between 10-150% of the dynamic range of the variable on each dimension.

Step (3) Evaluation function (fitness function in GA) values need to be defined for each particle in order to find its merit. The evaluation function is defined as

$$\min \sum_{i=1}^{N} F_i(P_i) + \alpha \left[\sum_{i=1}^{N} P_i - (P_D + P_L) \right]^2 \tag{11}$$

Here, α is the penalty parameter; the second term imposes a penalty on the particle in terms of increased cost, if power balance constraint is not satisfied. The first term is calculated using (5) for solution without considering valve point effects and (6) is applied when non smooth cost function due to valve point effects is considered.

Step (4) These values are set as the initial Pbest value of the particles.

Step (5) The best value among all the Pbest values, gbest, is identified.

Step (6) New velocities for all the dimensions in each particle are calculated using Eq. (6).

Step (7) The position of each particle is updated using Eq. (7).

Step (8) The objective function values are calculated for the updated positions of the particles. If the new value is better than the previous Pbest, the new value is set to Pbest.

Step (9) If the stopping criteria are met, the positions of particles represented by gbest are the optimal solution. Otherwise, the procedure is repeated from step (3).

IV. RESULTS AND ANALYSIS

The effectiveness of the PSO algorithm for economic dispatch solution with valve point loading effects is demonstrated on a three generating unit system. The results obtained are compared with results of real coded GA using the same evaluation function and particle definition, to compare their performance and solution quality and convergence efficiency. The software was written in MATLAB 8.3 platform and tested on Pentium IV. 1.5 GHz., 256 MB RAM personal computers. The PSO method is found to be sensitive to tuning parameters but its solution quality is better. PSO also converges in lesser time as there are no selection and crossover operations to be performed in this method.

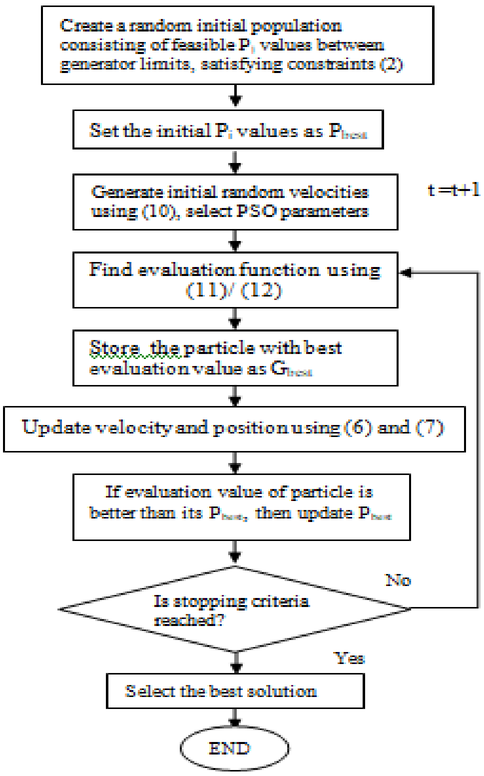

Fig. 1. Flowchart of proposed PSO algorithm for ELD

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A. Result of ELD without valve point effects

A simple PSO was applied to find out the optimal generation allocation for thee generating unit power system with power balance and unit operating constraint given in (2). The cost function defined by (3) is employed as evaluation function of PSO. Cost coefficients and limits on generating units are listed in Table I. The B coefficients for loss evaluation are given below.

$$[B]=\begin{bmatrix} 0.006760 & 0.000953 & -0.000507 \\ 0.000953 & 0.005210 & 0.000901 \\ -0.000507 & 0.000901 & 0.029400 \end{bmatrix}$$

B. Result of ELD with valve point effects

The classical lamda iteration method does not perform well with non smooth cost function resulting due to valve point effects. Hence, result of PSO based approach is compared with RGA. The cost function defined by (4) is employed as evaluation function of PSO algorithm. Step 1 to step 9 of the PSO algorithm listed in the previous section are applied for searching the optimal cost and corresponding generation allocation. The stopping criteria used is pre decided number of iterations here for comparison with GA. Actually, the velocity and position update procedure is continued in steps till the change in maximum fitness becomes smaller than a set tolerance value.

Table I Generator operating limits and cost coefficients

Variable / Generator	ai	bi	ci	ei	fi	Pimax	Pimin
Unit1	.00156	7.92	561	300	.031	600	100
Unit2	.00194	7.85	310	200	.042	400	100
Unit3	.00482	7.97	78	150	.063	200	50

Table II Parameters of PSO

Inertia weight W_{MAX}, W_{MIN}	C_1, C_2	Population size	Generations
0.9 – 0.4	2,2	100	100

Table III Ga parameters for eld without valve point loading

Population	Generation	Mutation Probability	Crossver Probability
100	100	0.3	0.9

Table IV Results of generation allocation without valve point loading

P_D (MW)	Method	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	PL (MW)	Cost (Rs/h)
750	Classical	329.63	295.11	142.78	17.54	7451.30
	RGA	367.4	288.66	113.35	19.412	7462.60
	PSO	347.47	322.29	99.02	18	7457.63
850	Classical	377.59	381.28	113.76	22.64	8406.80
	RGA	430.09	321.84	122.04	23.959	8411.62
	PSO	377.59	381.28	113.76	22.64	8414.80
950	Classical	504.13	400	70.96	25.10	9397.70
	RGA	456.55	380.44	144.34	31.957	9407.00
	PSO	451	400	129	30.77	9404.57

Table V Comparison of Pso Performance with Ga With Valve Point Loading

P_D	Method	$P_{G1(MW)}$	P_{G2} (MW)	P_{G3} (MW)	PL (MW)	Cost (Rs/h)
750	PSO	317.96	400.00	50	17.963	7658.60
	RGA	398.78	245.79	125.88	20.44	7667.50
850	PSO	297.88	380.22	200.00	28.10	8660.00
	RGA	481.99	245.66	149.33	26.99	8681.20
950	PSO	600	334.35	50	34.34	9609.30
	RGA	517.64	317.72	147.61	36.52	9682.00

TABLE VI Effect of Population Size on Pso Performance

Demand (MW)	Population Size	Method	Cost (Rs/h)	CPU Time (Sec)
750	20	GA	7465	0.0961
		PSO	7460	0.0632
750	40	GA	7467	0.1061
		PSO	7462	0.0832
750	60	GA	7460	0.112
		PSO	7454	0.0982
750	80	GA	7450	0.117
		PSO	7448	0.101
750	100	GA	7443	0.142
		PSO	7440	0.121

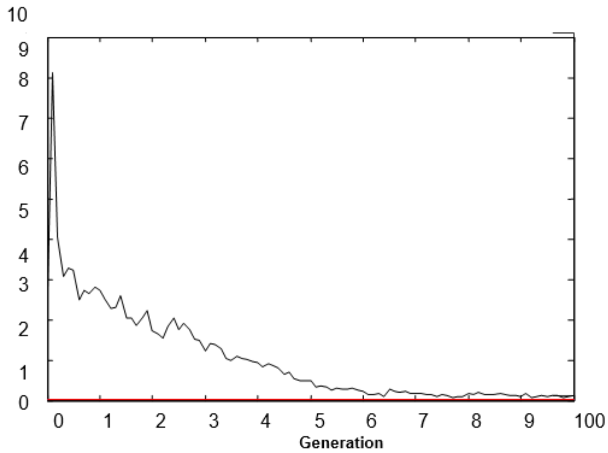

Fig. 2. Convergence characteristic of PSO for ELD (valve point loading)

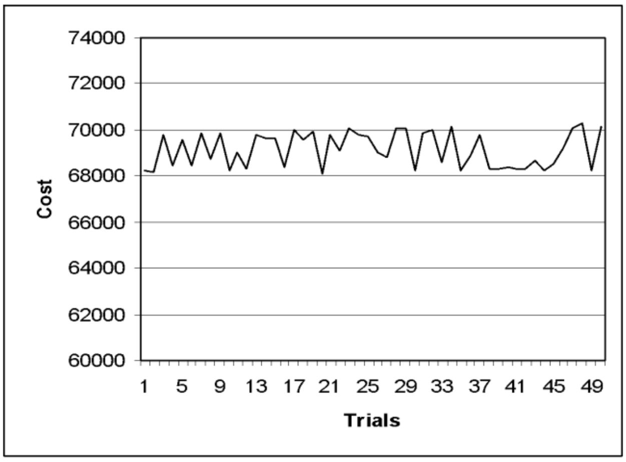

Fig. 3. Performance of PSO in different trials (Demand PD=700 MW)

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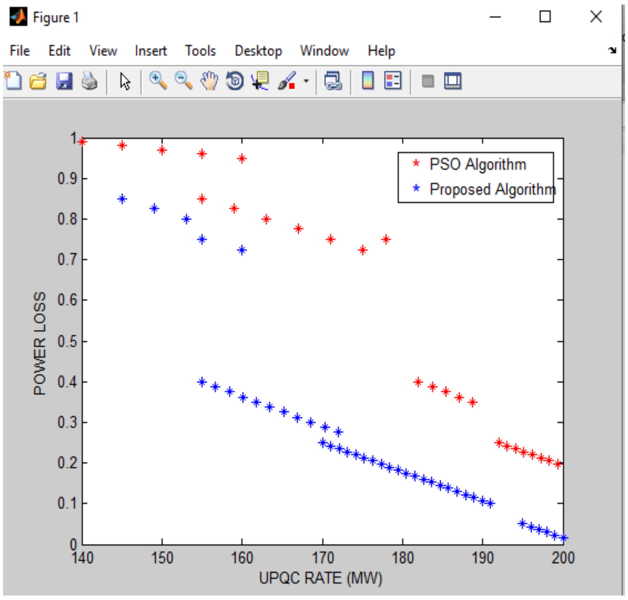

Fig. 4. Power loss, PSO vs MPSO

Figure 4 indicating power losses versus UPQC rate in the event of PSO and modified MPSO. Simulation results show that MOPSO optimized power loss and economics load dispatch in considering situation.

V. CONCLUSION

This paper presents a Particle swarm optimization based approach for solving the economical dispatch problem with valve point loading effect. The generator cost function in this case is non smooth which makes the problem a complex one with multiple minima. Classical gradient based methods cannot be applied in such cases. On the other hand, evolutionary programming methods such as GA and PSO, due to their stochastic nature, do not always converge to the same minima. However, it is observed that these methods achieve solutions very near to the global minima, in a very short time due to their simplicity. PSO is found to produce high quality solution in a shorter time, as compared to RGA based approach. Test results demonstrate that the PSO algorithm is not much dependent on the initial population and size of population as it is able to achieve near global results for all the tested cases.

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AUTHORS PROFILE

Anita Sahni, Research Scholar of RGPV university Bhopal (M.P.). She is pursuing her ME under the guidance of Dr.K.T. Chaturvedi. She completed her Bachelor of Engineering from SRMSCET Bareilly (U.P.) in 2015 from UPTU University. Her area of interest is soft computing techniques for economic load dispatch in Power System.

Dr. K. T. Chaturvedi, is Assistant professor in RGPV university Bhopal in the department of Electrical & Electronics Engineering. He has completed his Bachelor of Engineering from the MITS Gwalior (M.P.) in 2000, Master of Technology from MITS Gwalior (M.P.) in 2005,then he completed his PhD from RGPV university in 2009 with the title of "Power system optimization and security assessment using soft computing techniques" .He has published various research papers in International and national journals. He also communicated in national and international conferences.