Nonconvex Economic Load Dispatch by Enhanced Particle Swarm Optimization

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Abstract — *Economic load dispatch (ELD) is one of the main tools for optimal operation and planning of modern power systems. To solve effectively the ELD problem, most of the conventional calculus methods rely on the assumption that the fuel cost characteristic of a generating unit is a smooth and convex function, resulting in inaccurate dispatch. This paper explores the use of an enhanced particle swarm optimizer (EPSO) for the solution of the economic load dispatch problem by considering the valve-point effect and multi-fuel options, making the modeling of the generation cost functions more practical. Modification in the design of the inertia weight parameter of the conventional PSO is suggested to enhance the global search capability and avoid local minima. Experimental results show that the proposed EPSO approach outperforms other heuristic techniques in terms of solution quality and robustness.*

Keywords–*Nonconvex Economic Load Dispatch, Particle Swarm Optimization, Valve-Point Effect, Multi-fuel options.*

1. INTRODUCTION

The conventional economic load dispatch (ELD) problem of power generation involves allocation of power generation to different thermal units to minimize the operating cost subject to diverse equality and inequality constraints of the power system. This makes the ELD problem a large-scale highly nonlinear constrained optimization problem.

It is therefore of great importance to solve this problem as quickly and accurately as possible. The ELD problem has been solved via many traditional optimization methods, such as: Gradient-based techniques, Newton methods, linear programming, and quadratic programming. Unfortunately, the input-output characteristics of modern units are inherently nonlinear and nonconvex because of valve-point loadings, prohibited operating zones and multiple fuels, and furthermore they may generate multiple local minimum points in the cost function. Conventional techniques offer good results, but when the search space is nonlinear and has discontinuities, these techniques become difficult to solve with a slow convergence ratio and not always seeking to the global optimal solution. New numerical methods are then needed to cope with these difficulties, specially, those with high speed search to the optimal and not being trapped in local minima.

Several heuristic tools have evolved in the last decades that have facilitated solving the ELD problems with non-smooth cost functions. These tools are mainly: genetic algorithms [1], evolutionary programming [2], neural networks [3], simulated annealing [4], tabu search [5] and particle swarm optimization [6].

Particle swarm optimization (PSO) refers to a relatively new family of algorithms that may be used to find optimal or near optimal solutions to numerical and qualitative problems. PSO was introduced by Russell Ebehart and James Kennedy in 1995 [7], inspired by social behavior of bird flocking and fish schooling. PSO has proven to be both very fast and effective when applied to a diverse set of optimization problems.

In the PSO algorithm, the most important control parameter is the inertia weight ω. The role of this control parameter is considered to be crucial for the convergence of PSO [8]. For that, a new design of the inertia weight parameter is proposed in this paper in order to improve the global search capability and avoid the premature convergence to local minima.

In this work, a solution methodology based on the enhanced particle swarm optimization (EPSO) technique is developed and applied to solve the economic load dispatch problem in the presence of generating units with non-smooth cost functions. Simulation results on three test systems: the 3-generators system, 13-generators system and 10-generators systems are presented and compared to those given by other heuristic methods. Numerical results confirm that the proposed EPSO is superior to the other heuristic techniques in terms of solution quality and robustness.

2. NONCONVEX ECONOMIC LOAD DISPATCH

The classical economic dispatch problem is an optimization problem that determines the power output of each online generator that will result in a least cost system operating state. The ELD problem can then be written in the following form:

$$\text{Minimize} \quad f(x) \tag{1}$$
$$\text{Subject to:} \quad g(x) = 0 \tag{2}$$
$$h(x) \leq 0 \tag{3}$$

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

A. Objective function

The objective of the ELD is to minimize the total system cost by adjusting the power output of each of the generators connected to the grid. The total generation cost function $f(x)$ is usually expressed as a quadratic polynomial:

$$f(x) = \sum_{i=1}^{ng} a_i + b_i P_{gi} + c_i P_{gi}^2 \qquad [\$/h] \tag{4}$$

where ng is the number of online thermal units, P_{gi} is the active power generation at unit i and a_i, b_i and c_i are the cost coefficients of the i^{th} generator.

Generally, large power generators have multiple steam admission valves that are used to control the power output of the unit. When a steam admission valve starts to open, a sharp increase in losses occurs, which results in ripples in the unit's cost function [1]. Valve-point effects are usually modeled by adding a recurring rectified sinusoid to the basic quadratic cost curve [1]:

$$f(x) = a_i + b_i P_{gi} + c_i P_{gi}^2 + \left| d_i \sin\left(e_i (P_{gi}^{\min} - P_{gi})\right) \right| \tag{5}$$

where d_i and e_i are the coefficients of generator i reflecting valve point effects. $P_{gi}^{\min}$ is the minimum generation limit of unit i.

Moreover, there are many thermal generating units that can be supplied by multiple fuel sources [3]. In those cases, it is more appropriate to represent the unit's fuel cost characteristic as a piecewise function, reflecting the effects of fuel type changes. To obtain an accurate and practical ELD solution, valve-point effects and multi-fuel options should be included in the cost function which is formulated as follows [9]:

$$f(x) = a_{ij} + b_{ij} P_{gi} + c_{ij} P_{gi}^2 + \left| d_{ij} \sin\left(e_{ij} (P_{gi}^{\min} - P_{gi})\right) \right|, \quad \text{if } P_{i,j}^{\min} \leq P_i \leq P_{i,j}^{\max}, \quad j = 1, \ldots, nf \tag{6}$$

where i and j denote the index of unit and index of fuel type, respectively; a_{ij}, b_{ij}, c_{ij}, d_{ij} and e_{ij} are the cost coefficients of the unit i for fuel type j; $P_{i,j}^{\min}$ and $P_{i,j}^{\max}$ are the minimum and maximum power output of unit i with fuel option j, respectively, and nf is the number of fuel types for each unit.

B. Equality constraints

The equality constraint is represented by the power balance constraint that reduces the power system to a basic principle of equilibrium between total system generation and total system loads. Equilibrium is only met when the total system generation $\sum_{i=1}^{ng} P_{gi}$ equals the total system load P_D plus system losses P_L as it is shown in (7):

$$\sum_{i=1}^{ng} P_{gi} - P_D - P_L = 0 \tag{7}$$

The exact value of the system losses can only be determined by means of a power flow solution. The most popular approach for finding an approximate value of the losses is by way of Kron's loss formula (8), which approximates the losses as a function of the output level of the system generators.

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_{gi} B_{ij} P_{gi} + \sum_{i=1}^{ng} P_{gi} B_{i0} + B_{00} \tag{8}$$

where B_{ij}, B_{io} and B_{oo} are the loss coefficients.

C. Inequality constraints

Generating units have lower ($P_{gi}^{\min}$) and upper ($P_{gi}^{\max}$) production limits, which are directly related to the design of the machine. These bounds can be defined as a pair of inequality constraints, as follows:

$$P_{gi}^{\min} \leq P_{gi} \leq P_{gi}^{\max} \tag{9}$$

3. OVERVIEW OF PARTICLE SWARM OPTIMIZATION (PSO)

The PSO is a swarm intelligence method that differs from well-known evolutionary computation algorithms, such as genetic algorithms (GA), in that the population is not manipulated through operators inspired by the human DNA procedures. Instead, in PSO, the population dynamics simulate the behavior of a "birds' flock", where social sharing of information takes place and individuals profit from the discoveries and previous experience of all other companions during the search for food. Thus, each companion, called *particle*, in the population, which is called *swarm*, is assumed to "fly" over the search space looking for promising regions on the landscape. For a minimization case, such regions possess lower function values than others previously visited. In this context, each particle is treated as a point into the search space, which adjusts its own flying according to its flying experience as well as the flying experience of other particles. Therefore, each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) that it has achieved so far. This implies that each particle has a memory, which allows it to remember the best position on the feasible search space that it has ever visited. This value is commonly called *Pbest*. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighborhood of the particle. This location is commonly called *Gbest*. The basic idea behind the particle swarm optimization technique consists, at each iteration, updating the velocity and accelerating each particle towards *Pbest* and *Gbest* locations.

The velocity of each particle can be modified by using the following equation [6, 7]:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (Pbest_i^k - X_i^k) + c_2 r_2 (Gbest^k - X_i^k) \quad (10)$$

where,

V_i^k velocity of particle *i* at iteration *k*,

X_i^k position of particle *i* at iteration *k*

$Pbest_i^k$ best position of particle *i*,

$Gbest^k$ best position of the group,

ω inertia weight parameter,

c_1, c_2 positive constants,

r_1, r_2 random numbers within the range [0, 1].

The position of each particle is updated by the following equation [6, 7]:

$$X_i^{k+1} = X_i^K + V_i^{k+1} \quad (11)$$

The positive constants c_1, c_2 provide the correct balance between exploration and exploitation, and are called the cognitive parameter and the social parameter, respectively. The random numbers provide a stochastic characteristic for the particles velocities in order to simulate the real behavior of the birds in a flock.

The weight parameter ω is a control parameter which is used to control the impact of the previous history of velocities on the current velocity of each particle. Hence, the parameter ω regulates the trade-off between global and local exploration ability of the swarm [10]. The recommended value of the inertia weight ω is to set it to a large value for the initial stages, in order to enhance the global exploration of the search space, and gradually decrease it to get more refined solutions facilitating the local exploration in the last stages. In general, the inertia weight factor is set according to the following equation [6]:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} iter \quad (12)$$

where,

$\omega_{\min}$, $\omega_{\max}$ initial and final weights,

$iter_{\max}$ maximum number of iterations,

$iter$ current iteration number.

The velocity of each particle is limited by a maximum value $V_i^{\max}$ which facilitates local exploration of the problem space and it realistically simulates the incremental changes of human learning. This limit is given by:

$$V_i^{\max} = \frac{X_i^{\max} - X_i^{\min}}{N} \quad (13)$$

where $X_i^{\min}$ and $X_i^{\max}$ are the minimum and maximum position limits of the particle *i*. *N* is a defined number of intervals.

4. ENHANCED PARTICLE SWARM OPTIMIZATION (EPSO)

The inertia weight parameter ω is generally the key factor affecting the PSO's convergence. This parameter plays the role of balancing the global search and local search capability of PSO. It can be a positive constant or even a positive linear or non linear function of time. Usually, the inertia weight parameter is linear decreasing during the iterations according to (12).

Improvements in original PSO can be powerful to escape more easily from local minima. In this context, the enhanced PSO (EPSO) proposed in this paper uses a new inertia weight parameter ω' given by (14) which is based on sinusoidal and exponential functions.

$$\omega' = \left| \alpha \exp(-\beta\, iter) \cos(\gamma\, iter) \right| \quad (14)$$

where α, β and γ are positive constants.

While the conventional inertia factor ω decreases linearly from $\omega_{\min}$, $\omega_{\max}$, the suggested new weight decreases while oscillating during the iterations as shown in Fig. 1 for $iter_{\max} = 150$, $\omega_{\min} = 0.4$, $\omega_{\max} = 0.9$, $\alpha = 1.5$, $\beta = 0.02$ and $\gamma = 10$.

5. ENHANCED PSO (EPSO) ALGORITHM

The enhanced PSO algorithm (EPSO) applied in this study for ELD problem can be described as follows:

Step 1: Generate randomly the particles between the maximum and minimum operating limits of the generating units.

Step 2: Generate the particle velocities randomly.

Step 3: Evaluate the fitness function of each particle. *Pbest* is set to the initial positions of step 1.

Step 4: Search for *Gbest* among *Pbest* using the evaluated fitness functions.

Step 5: Compute the particle velocities using (10) and (14).

Step 6: Update the particle positions using (11).

Step 7: Evaluate the new fitness functions for the updated particle positions. For each particle *i*, if the new fitness value is better than the one associated with $Pbest_i$, than the new position is set to $Pbest_i$. If one of the stopping criteria is met, than stop and the actual particle positions represent the optimal solution. Otherwise, the procedure is repeated from step 4.

The stopping criteria are the conditions under which the search process will stop. In this work, the search procedure will terminate whenever the predetermined maximum number of iterations $iter_{\max}$ is reached, or whenever the global best solution does not improve over a predetermined number of iterations.

In the fitness evaluation, penalty functions can be used whenever there are violations to some equality and/or inequality constraints [11]. Basically, the objective function $f(x)$ is substituted by a fitness function $f^{'}(x)$ that penalizes the fitness whenever the solution contains parameters that violate the problem constraints,

$$f^{'}(x) = f(x) + Penalty(x) \tag{15}$$

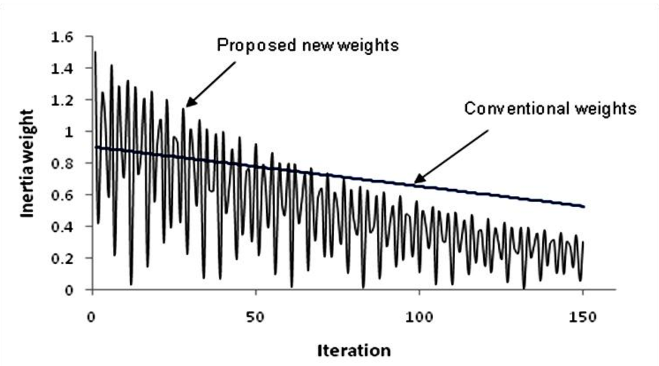

Figure 1. Comparison of inertia weight parameter

In this paper, the exterior penalty function method is applied to the equality constraints [11]. The new objective function is than given by:

$$f^{'}(x) = f(x) + \sum_{i=1}^{m} K_i \left[g_i(x)\right]^2 \tag{16}$$

where K_i is a positive constant. To satisfy the i^{th} constraint, we increase K_i from zero to infinity to give more and more weightings. The specification of these weighting factors depends on how strongly we feel about satisfying the constraints.

6. Simulation Results

The feasibility of the proposed EPSO approach was tested on three different test systems: 3, 13 and 10 generating units which are described in [2] and [9]. Simulations were carried out using MATLAB computational environment, on a personal computer with Intel Pentium IV 3.0 GHz processor and 512 MB total memory.

Case 1.

This case consisted of 3 generating units, of which the input data are tabulated in Table 1. The total load demand of the system is 850 MW [2]. The system is considered as lossless and only the generation capacity constraints are considered. The control parameter settings of EPSO are given in Table 2. The best solution obtained using EPSO is given in Table 3 which is compared with the best results found by genetic algorithm (GA) [1], evolutionary programming (EP) [12] and particle swarm optimization (PSO) [6]. As it can be observed, the results are identical to those found by EP and PSO techniques, showing that EPSO is capable of solving efficiently problems featuring valve point effects.

The variation of the total generation cost of the best solution during the optimization process is shown in Fig. 2. The convergence of this last solution was obtained after 0.020 seconds and 100 iterations.

TABLE 1. UNITS DATA FOR TEST CASE 1

Gen.	P_{gmax} **(MW)**	P_{gmin} **(MW)**	***a***	***b***	***c***	***d***	***e***
1	100	600	561	7.92	0.001562	300	0.0315
2	100	400	310	7.85	0.001940	200	0.0420
3	50	200	78	7.97	0.004820	150	0.0630

TABLE 2. EPSO CONTROL PARAMETER SETTINGS (CASE 1)

Parameter	**Setting**
Number of particles	20
Maximum number of iterations	500
Inertia weight constants (*α*, *β*, *γ*)	(1.5, 0.02, 10.0)
Acceleration factors (c_1, c_2)	(2.0, 2.0)
Number of intervals (*N*)	10
Penalty factor (*K*)	150

TABLE 3. COMPARISON OF THE BEST RESULTS FOR CASE 1

Power	GA [1]	EP [12]	PSO [6]	**EPSO**
P_{g1}	300.00	300.26	300.27	**300.27**
P_{g2}	400.00	400.00	400.00	**400.00**
P_{g3}	150.00	149.74	149.73	**149.73**
Total power (MW)	850.00	850.00	850.00	**850.00**
Total fuel cost ($/h)	8237.60	8234.07	8234.07	**8234.07**

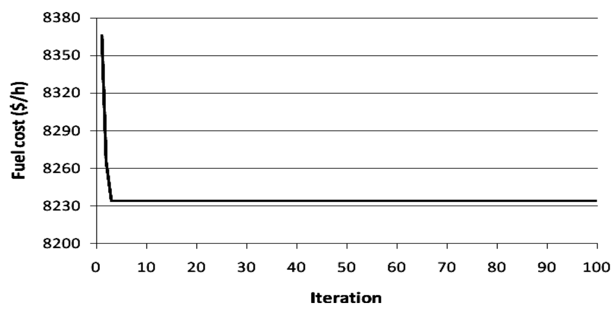

Figure 2. Convergence of the best solution (case 1)

Case 2.

This case consisted of 13 generating units. The cost coefficients of the generators are listed in Table 4. The demanded load is 1800 MW. In this case the solution space is highly nonlinear and contains more local minima compared to that of case 1. In order to illustrate the efficiency and robustness of the proposed algorithm, 50 independent runs were performed using the adapted control parameter settings listed in Table 5. The obtained results are summarized in Table 6, and compared to those found by improved fast evolutionary programming (IFEP) [2], PSO and personal best oriented PSO (PPSO) [13], Hybrid PSO–SQP [14], hybrid differential evolution algorithm (HDE) [15] and hybrid multi-agent based PSO (HMAPSO) [16]. The best economic dispatch solution obtained with EPSO is shown in Table 7. The convergence of the algorithm for the trial run that generated the minimum cost was achieved after 0.26 seconds and 800 iterations as shown in Fig. 2.

From Table 6, it is clear that EPSO is superior to the other heuristic techniques and gives the best cost values, in a very short time. Among the 50 trial runs, 47 were under 18100.00 $/h (94%), with the minimum cost of 17963.85 $/h and a standard deviation of 66.50 $/h, indicating a good convergence characteristic (see Fig. 4). It can be concluded that EPSO algorithm is more robust and computationally effective in solving the ELD problem considering valve-point loading effects.

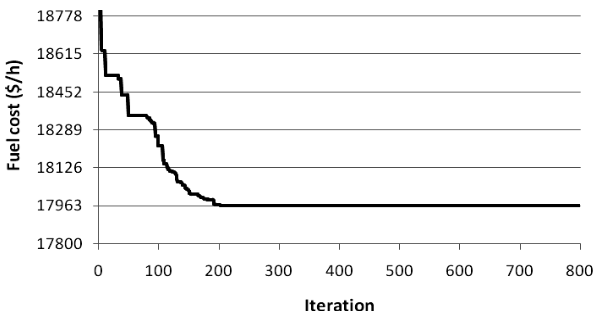

Figure 3. Convergence of the best solution for case 2

TABLE 4. UNITS DATA OF THE 13 GENERATING UNITS

Gen.	P_{gmax} (MW)	P_{gmin} (MW)	*a*	*b*	*c*	*d*	*e*
1	0	680	550	8.10	0.00028	300	0.035
2	0	360	309	8.10	0.00056	200	0.042
3	0	360	307	8.10	0.00056	200	0.042
4	60	180	240	7.74	0.00324	150	0.063
5	60	180	240	7.74	0.00324	150	0.063
6	60	180	240	7.74	0.00324	150	0.063
7	60	180	240	7.74	0.00324	150	0.063
8	60	180	240	7.74	0.00324	150	0.063
9	60	180	240	7.74	0.00324	150	0.063
10	40	120	126	8.60	0.00284	100	0.084
11	40	120	126	8.60	0.00284	100	0.084
12	55	120	126	8.60	0.00284	100	0.084
13	55	120	126	8.60	0.00284	100	0.084

TABLE 5. EPSO CONTROL PARAMETER SETTINGS (CASE 2)

Parameter	Setting
Number of particles	50
Maximum number of iterations	1000
Inertia weight constants (α, β, γ)	(1.6, 0.01, 10.0)
Acceleration factors (c_1, c_2)	(2.5, 1.4)
Number of intervals (*N*)	10

TABLE 6. COMPARISON OF RESULTS FOR CASE 2

Method	Min. cost ($/h)	Max. cost ($/h)	Mean cost ($/h)	Mean time (s)
IFEP [2]	17994.07	18267.42	18127.06	157.43
PSO [13]	18014.16	18249.89	18104.65	–
PPSO [13]	17971.01	18246.70	18106.33	–
PSO-SQP [14]	17969.93	–	18029.99	33.97
HDE [15]	17975.73	–	18134.80	–
HMAPSO [16]	17969.31	17969.31	17969.31	1.50
EPSO	**17963.85**	**18222.24**	**18030.32**	**0.32**

TABLE 7. THE BEST ECONOMIC DISPATCH SOLUTION OF EPSO FOR CASE 2

Power	EPSO
$P_{g\,1}$	628.32
$P_{g\,2}$	149.48
$P_{g\,3}$	222.88
$P_{g\,4}$	109.86
$P_{g\,5}$	109.87
$P_{g\,6}$	109.87
$P_{g\,7}$	60.00
$P_{g\,8}$	109.87
$P_{g\,9}$	109.87
$P_{g\,10}$	40.00
$P_{g\,11}$	40.00
$P_{g\,12}$	55.00
$P_{g\,13}$	55.00
Total power (MW)	**1800.00**
Total fuel cost ($/h)	**17963.85**

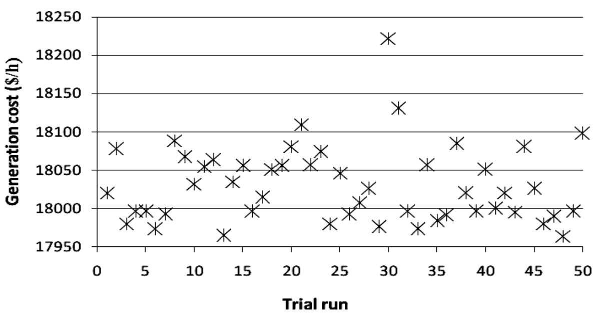

Figure 4. Generation cost of the 50 trial runs for case 2

Case 3.

To further investigate the performance of the proposed EPSO, experiments are performed on a more complex test system having ten generators, which considers valve-point loading effects and multi-fuel options [9]. The first generator of the system has two fuel options and the remaining generators have three fuel options each. The total system demand is 2700 MW and no transmission losses are considered. The input data and related constraints of the test system are described in [9]. Note that the unit curves of this system have non-differential points according to valve-point loading and multiple fuel changes. The control parameters of EPSO are the same as those used in case 2. The best solution produced in the 50 trials was 623.72 $/h. The worst solution obtained was 624.31 $/h with an average of 624.07 $/h. The average execution time required for one complete solution was 0.42 s, which is very tolerable for ELD solutions. Also, it is important to point out that for all the trial runs, the convergence was reached without any violation of the generator capacity constraints. The global optimal dispatch solution given by EPSO is summarized in Table 8, which converged after 250 generations and 0.42 s. The convergence characteristic of the EPSO is depicted in Fig. 5.

The results of the proposed approach were compared in Table 9 to those reported using conventional GA with multiplier updating (CGA-MU) [9], improved GA with multiplier updating (IGA-MU) [9], new PSO with local random search (NPSO-LRS) [17], anti-predatory PSO (APSO1) [18], adaptive PSO (APSO2) [19], combined PSO with real-valued mutation (CBPSO-RVM) [20]. From this table, it can be seen that the results given by EPSO are better than those reported in the literature.

TABLE 8. BEST RESULTS OF EPSO FOR 10-UNIT SYSTEM (CASE 3)

Unit	P_i^{min}	P_i^{max}	Fuel type	Generation (MW)
1	100	250	**2**	**215.10**
2	50	230	**1**	**212.46**
3	200	500	**1**	**278.20**
4	99	265	**3**	**265.00**
5	190	490	**1**	**276.40**
6	85	265	**3**	**240.73**
7	200	500	**1**	**282.54**
8	99	265	**3**	**240.79**
9	130	440	**3**	**424.68**
10	200	490	**1**	**264.07**
Total generation (MW)				**2700.000**
Total fuel cost ($/h)				**623.72**

TABLE 9. COMPARISON RESULTS FOR CASE 3

Method	Minimum cost ($/h)	Maximum cost ($/h)	Mean cost ($/h)
CGA-MU [9]	624.72	633.87	627.61
IGA-MU [9]	624.52	630.87	625.87
NPSO-LRS [17]	624.13	627.00	625.00
APSO1 [18]	624.01	627.30	624.82
APSO2 [19]	623.91	NA	624.51
CBPSO-RVM [20]	623.96	624.29	624.08
Proposed EPSO	**623.72**	**624.31**	**624.07**

NA: Not Available.

The statistical results of 50 runs by EPSO with 50 different initial trial solutions are depicted in Fig. 6. From this figure, it is observed that the EPSO algorithm consistently produces solutions at or very near to the global optimum, indicating a good convergence characteristic. It can be concluded that EPSO algorithm is robust and effective in solving the ELD problem considering practical generator operation constraints, such us valve-point effects and multiple fuel changes.

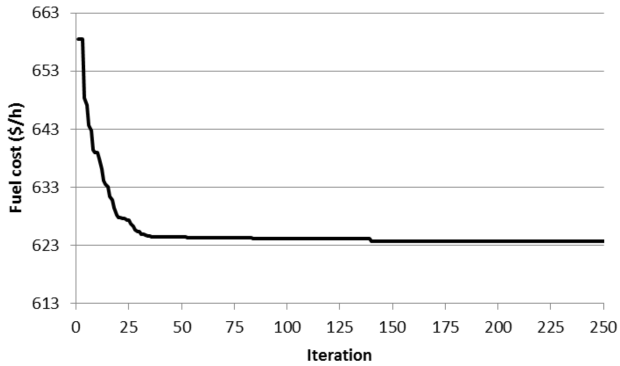

Figure 5. Convergence behavior of EPSO for case 3

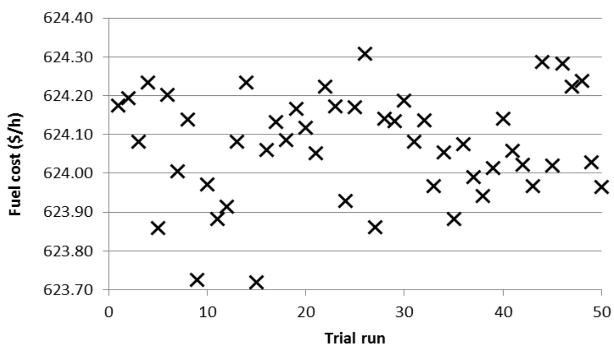

Figure 6. Fuel cost distribution obtained by EPSO (case 3)

7. Conclusion

In this paper, a new approach based on the enhanced particle swarm optimization (EPSO) was developed and successfully applied to solve the nonsmooth and nonconvex economic load dispatch problem taking into account valve-point loading effects and multi-fuel options. In order to improve the global and local search abilities of the proposed EPSO, a new inertia weight parameter has been suggested.

The feasibility of the proposed EPSO was demonstrated on three test systems consisting of 3, 13 and 10 generating units. Simulation results have demonstrated that the proposed improvement was a powerful strategy to prevent premature convergence to local minima, providing high quality solutions. Also, simulation results confirm that the proposed EPSO is superior to the other heuristic techniques in terms of solution quality and robustness.

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