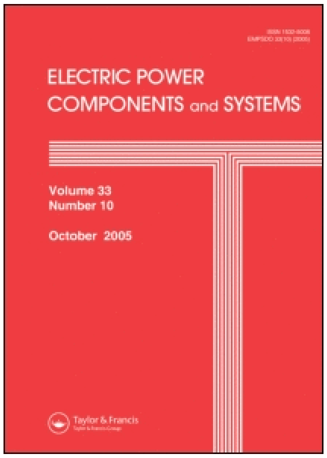

Electric Power Components and Systems
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713399721

Solution of Different Types of Economic Load Dispatch Problems Using a Pattern Search Method

J. S. Al-Sumait [a]; J. K. Sykulski [a]; A. K. Al-Othman [b]
[a] Electrical Power Engineering Group, University of Southampton, Highfield, Southampton, United Kingdom
[b] Electrical Engineering Department, College of Technological Studies, Alrawda, Kuwait

Online Publication Date: 01 March 2008
To cite this Article: Al-Sumait, J. S., Sykulski, J. K. and Al-Othman, A. K. (2008) 'Solution of Different Types of Economic Load Dispatch Problems Using a Pattern Search Method', Electric Power Components and Systems, 36:3, 250 - 265
To link to this article: DOI: 10.1080/15325000701603892
URL: http://dx.doi.org/10.1080/15325000701603892

Electric Power Components and Systems, 36:250–265, 2008

ISSN: 1532-5008 print/1532-5016 online
DOI: 10.1080/15325000701603892

Taylor & Francis
Taylor & Francis Group

Solution of Different Types of Economic Load Dispatch Problems Using a Pattern Search Method

J. S. AL-SUMAIT,[1] J. K. SYKULSKI,[1] and
A. K. AL-OTHMAN[2]

[1]Electrical Power Engineering Group, University of Southampton, Highfield Southampton, United Kingdom
[2]Electrical Engineering Department, College of Technological Studies, Alrawda, Kuwait

Abstract *Direct search (DS) methods are evolutionary algorithms used to solve constrained optimization problems. DS methods do not require information about the gradient of the objective function when searching for an optimum solution. One such method is a* pattern search *(PS) algorithm. This study presents a new approach based on a constrained PS algorithm to solve various types of power system economic load dispatch (ELD) problems. These problems include economic dispatch with valve point (EDVP) effects, multi-area economic load dispatch (MAED), companied economic-environmental dispatch (CEED), and cubic cost function economic dispatch (QCFED). For illustrative purposes, the proposed PS technique has been applied to each of the above dispatch problems to validate its effectiveness. Furthermore, convergence characteristics and robustness of the proposed method has been assessed and investigated through comparison with results reported in literature. The outcome is very encouraging and suggests that PS methods may be very efficient when solving power system ELD problems.*

Keywords ELD, DS method, PS method, evolutionary algorithms, optimization

1. Introduction

Scarcity of energy resources, increasing power generation costs, and ever-growing demand for electric energy necessitates optimal economic dispatch (ED) in today's power systems. The main objective of ED is to reduce the total power generation cost while satisfying various equality and inequality constraints. Traditionally, in ED problems, the cost function for generating units has been approximated as a quadratic function.

A variety of optimization techniques has been applied in solving ELD problems. Some of these techniques are based on classical optimization formulations, while others are based on artificial intelligence methods or heuristic algorithms. Many references present the application of classical optimization methods, such as linear or quadratic programming, to solve ELD problems [1, 2]. Classical optimization methods are reported to be highly sensitive to the selection of the starting points and sometimes converge to a

Received 12 October 2006; accepted 13 July 2007.
Address correspondence to Dr. Abdrulrahman Al-Othman, Electrical Engineering Department, College of Technological Studies, P.O. Box 33198, Alrawda, 73452, Kuwait. E-mail: ak.alothman@paaet.edu.kw

local optimum or diverge altogether. Linear programming methods are fast and reliable, but have disadvantages associated with the piecewise linear cost approximation. Non-linear programming methods are known to have problems of convergence and algorithmic complexity. Newton-based algorithms struggle with handling a large number of inequality constraints [3]. Methods based on artificial intelligence techniques, such as artificial neural networks, are also presented [4, 5]. Heuristic search techniques, such as particle swarm optimization [3] and genetic algorithms [6], have also been successfully applied to ELD problems. Finally, hybrid methods have been developed, where the conventional Lagrangian relaxation approach, a first-order gradient method, and multi-pass dynamic programming (DP) are combined in [7].

Recently, a particular family of global optimization methods, originally introduced and developed by researchers in the 1960s [8], has attracted special attention. Known as DS methods, they are simply designed to explore a set of points around the current position, looking for a location that has a better objective value than the existing one. This family includes PS algorithms, simplex methods (different from the simplex used in linear programming), Powell optimization, and others [9].

DS methods, in contrast to more standard optimization methods, are often called derivative-free as they do not require information about the gradient or higher derivatives of the objective function to search for an optimal solution. Thus, DS methods are a popular choice to solve non-continuous, non-differentiable, and multimodal (*i.e.*, multiple local optima), optimization problems. Since the ED is one such problem, the proposed method appears to be a good candidate to achieve efficient solutions [10].

The main objective of this study is to introduce the use of a PS optimization technique in application to the power system ELD. The performance, effectiveness, and robustness of the proposed method are assessed via intensive testing and comparison with results reported in literature. The article is organized as follows: Section 2 introduces the problem formulation, Section 3 presents a description of the proposed PS algorithm, analysis and test results are presented in Section 4, followed by concluding remarks.

2. Problem Formulation

Generally, depending on the type of the ELD considered, the traditional formulation is basically a minimization of summation of the fuel costs of the individual dispatchable generators, subject to the real power balanced with the total load demand as well as with the limits on generators' outputs. The mathematical form of each type of ED problem considered in this study may be described as in the following subsections.

2.1. Mathematical Form of EDVP

The inclusion of the valve-point effects is advantageous and makes the modeling of the fuel-cost function more realistic [11–13]. However, the valve-point effects, which appear as a sinusoidal term added to the fuel-cost functions, introduce ripples to the heat-rate curve, and, therefore, create more local minima in the search space.

The objective function of an EDVP is to minimize F, where F is given by

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

The incremental fuel-cost function of the generation units with valve-point loadings are represented as follows [11]:

$$F_i(P_i) = a_i P_{gi}^2 + b_i P_{gi} + c_i + |e_i \times \sin(f_i \times (P_{gi_{(\min)}} - P_{gi}))| \tag{2}$$

subject to

$$\sum_{i=1}^{N} P_{gi} = P_D + P_L \tag{3}$$

$$P_{gi_{(\min)}} < P_{gi} < P_{gi_{(\max)}}, \qquad i \in N_s, \tag{4}$$

where

F is the system overall cost function;
N is the number of generators in the system;
a_i, b_i, and c_i are the constants of fuel function of generator number i;
e_i, f_i are the constants of the valve-point effect of generator number i;
P_{gi} is the active power generation of generator number i;
P_D is the total power system demand;
P_L is the total system transmission losses;
$P_{gi_{(\min)}}$ is the minimum limit on active power generation of generator i;
$P_{gi_{(\max)}}$ is the maximum limit on active power generation of generator i; and
N_s is the set of generators in the system.

2.2. *Mathematical Form of MAED*

In a MAED problem, the objective is to determine the most economical generation level in a given area and the power interchange between the areas that minimize the overall operation cost while satisfying a set of constraints as follows [14]:

$$\min\left[\sum F(P_{gi}) + \sum G(t_{jk})\right] \tag{5}$$

subject to

$$\sum_{i\in\alpha_m} P_{gi} + \sum_{j\in\beta_m} t_{kj} - \sum_{j\in\beta_m} t_{jk} - D_m = 0 \tag{6}$$

$$P_{gi_{(\min)}} \le P_{gi} \le P_{gi_{(\max)}} \tag{7}$$

$$t_{jk_{(\min)}} \le t_{jk} \le t_{jk_{(\max)}}, \tag{8}$$

where

$F(P_{gi})$ is the fuel-cost function of generator P_{gi},
$G(t_{jk})$ is the cost of transmission of line t_{jk},
t_{jk} is the economic flow on the tie line from area j to k,
α_m is the set of generating units in area m,
β_m is the set of tie lines in area m,
P_{gi} is the active power generation of generator number i,
D_m is the total load demand of area m,

P_L is the total system transmission losses,
$P_{gi_{(\min)}}$ is the minimum limit on active power generation of generator i,
$P_{gi_{(\max)}}$ is the maximum limit on active power generation of generator i,
$t_{jk_{(\min)}}$ is the minimum limit on active power generation of generator i, and
$t_{jk_{(\max)}}$ is the maximum limit on active power generation of generator i.

2.3. Mathematical Form of CEED

The primary objective of ED can be extended to take into consideration the environmental impact of power generation due to the emission of different pollutants that could inflict harm to the environment [15, 16]. The emission-cost function, just like the fuel-cost function in traditional ED, is modeled as a second-order polynomial

$$E = \sum_{i=1}^{N} d_i P_{gi}^2 + h_i P_{gi} + u_i \quad \text{(kg/h)} \tag{9}$$

where d_i, h_i, and u_i are emission coefficients of generator i. Thus, the overall objective function for the combined emission–economic dispatch is

$$\min\left[F + \frac{(1-w)}{w}E\right] \tag{10}$$

where w is a weighting factor, $w \in [0, \ldots, 1]$, which represents the relative importance or the trade-off between the fuel-cost function F and the emission-cost function E. The objective function of Eq. (10) is minimized, subject to the constraints given by Eqs. (3) and (4), where the transmission losses are given by

$$P_L = \sum_{n=1}^{N}\sum_{k=1}^{N} P_{gn} B_{n,k} P_{gk} \tag{11}$$

where B is a matrix of loss coefficients and P_{gn} and P_{gk} are the active power generation of generators n and k, respectively.

2.4. Mathematical Form of QCFED

Traditionally, the cost function of the generating units is approximated as a quadratic function. A crucial issue in ED studies is to determine the order and approximate the coefficients of the polynomial used to model the fuel-cost function [17]. This issue is particularly important in terms of reducing the error between the approximated polynomial, along with its coefficients, and the actual operating cost. According to [17, 18], a third-order (cubic) polynomial is realistic to model the operating cost. For a generating unit with non-monotonically increasing cost curves, a cubic polynomial is usually used to obtain accurate dispatch results [19]. The third-order polynomial function is expressed as

$$F_i(P_{gi}) = \alpha_{i,1} P_{gi}^3 + \alpha_{i,2} P_{gi}^2 + \alpha_{i,3} P_{gi} + \alpha_{i,4} \tag{12}$$

subject to

$$\sum_{i=1}^{N} P_{gi} = P_D + P_L \tag{13}$$

$$P_{gi_{(\min)}} < P_{gi} < P_{gi_{(\max)}}, \qquad i \in N_s, \tag{14}$$

where $\alpha_{i,1}$, $\alpha_{i,2}$, $\alpha_{i,3}$, and $\alpha_{i,4}$ are the coefficients of the cubic fuel-cost function.

System Losses Representation. It important to mention at this stage that the B-coefficients, or loss coefficients, have been adopted for the modeling of the system losses in the previous formulations. The representation of the system losses by B-coefficients is indeed constant and suitable for actual interpretation of the real power system losses under certain conditions. If the actual operating conditions are close to the base case where B-constants were computed, then the B-coefficients method should compute the system losses with reasonably high accuracy [20, 21]. In other words, the use of constant values for the loss coefficients in the transmission losses equation yields practically precise results when the coefficients are calculated for some average operating condition and if extremely wide shifts of load between plants or in total load do not occur. In practice, large systems are economically loaded by calculations based on just one set of loss coefficients that are sufficiently accurate throughout the daily variations of load on the system [21].

3. Overview of the PS Method

The PS optimization routine is an evolutionary technique that is suitable to solve a variety of optimization problems that lie outside the scope of the standard optimization methods. Generally, PS has the advantage of being very simple in concept, being easy to implement, and resulting in a computationally efficient algorithm. Unlike other heuristic algorithms, such as genetic algorithms (GA) [22, 23], PS possesses a flexible and well-balanced operator to enhance and adapt the global and fine tune the local search. A historic discussion of DS methods for unconstrained optimization is presented in [9], where a modern perspective on the classical family of derivative-free algorithms is given with focus on the development of DS methods.

The PS algorithm proceeds by computing a sequence of points that may or may not approach the optimal point. The algorithm starts by establishing a set of points called a *mesh* around the given point. This current point could be the initial starting point supplied by the user, or it could be computed from the previous step of the algorithm. The mesh is formed by adding the current point to a scalar multiple of a set of vectors called a *pattern*. If a point in the mesh is found to improve the objective function at the current point, the new point becomes the current point at the next iteration.

This may be better explained by the following:

First: The PS begins at the initial point X_0 that is given as a starting point by the user. At the first iteration, with a scalar $= 1$ called the *mesh size*, the pattern vectors are constructed as [0 1], [1 0], [−1 0], and [0 −1]; they may be called direction vectors. Then the PS algorithm adds the direction vectors to the initial point X_0 to compute the following mesh points:

$$X_0 + [1 \quad 0]; \qquad X_0 + [0 \quad 1]$$

$$X_0 + [-1 \quad 0]; \qquad X_0 + [0 \quad -1]$$

Figure 1 illustrates the formation of the mesh and pattern vectors. The algorithm computes the objective function at the mesh points in the order shown.

The algorithm polls the mesh points by computing their objective function values until it finds one whose value is smaller than the objective function value of X_0. If there is such a point, then the poll is successful and the algorithm sets this point equal to X_1.

After a successful poll, the algorithm steps to iteration 2 and multiplies the current mesh size by 2. (This is called the *expansion factor* and has a default value of 2.) The mesh at iteration 2 contains the following points: $2 * [1 \ 0] + X_1$, $2 * [0 \ 1] + X_1$, $2 * [-1 \ 0] + X_1$, and $2 * [0 \ -1] + X_1$. The algorithm polls the mesh points until it finds one whose value is smaller the objective function value of X_1. The first such point it finds is called X_2, and the poll is successful. Because the poll is successful, the algorithm multiplies the current mesh size by 2 to get a mesh size of 4 at the third iteration because the expansion factor = 2.

Second: If in iteration 3 (mesh size = 4) none of the mesh points have a smaller objective function value than the value at X_2, the poll is declared unsuccessful. In this case the algorithm does not change the current point at the next iteration, which is $X_3 = X_2$. At the next iteration, the algorithm multiplies the current mesh size by 0.5, a *contraction factor*, so that the mesh size at the next iteration is smaller. The algorithm then polls with a smaller mesh size.

The PS optimization algorithm will repeat the illustrated steps until it finds the optimal solution for the minimization of the objective function. The algorithm stops when any of the following conditions occurs:

- the mesh size is less than mesh tolerance,
- the number of iterations performed by the algorithm reaches a predefined maximum,

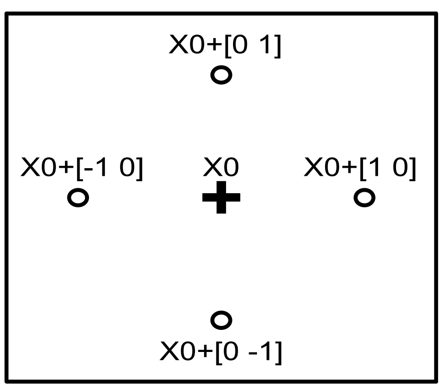

Figure 1. PS mesh points and the pattern.

- the total number of objective function evaluations performed by the algorithm reaches a predefined maximum,
- the distance between the point found at one successful poll and the point found at the next successful poll is less than a predefined tolerance, or
- the change in the objective function from one successful poll to the next successful poll is less than a predefined function tolerance.

Constraint Handling

Many ideas were suggested to insure that the solution will satisfy the constraints [24]. Currently, the only minor weakness in the nonlinear constraints handling procedure is due to the lack of specific information related to first-order derivatives. Although many systematic approaches have been employed to handle the nonlinear constraints, the augmented Lagrangian approach, which has been utilized by PS method, has overcome such shortcomings in dealing with nonlinear constraints. Lewis and Torczon [25] stated that, despite the absence of an explicit estimation of any derivatives (a characteristic of PS methods), PS-augmented Lagrangian approach exhibits all of the first-order convergence properties of the original algorithm advocated by Conn, Gould, and Toint [26, 27]. Lewis and Torczon [25] were able to overcome such drawbacks by proceeding with successive, inexact minimization of the augmented Lagrangian via PS methods, even without knowing exactly how inexact the minimization is. As a result, the size of the problem will increase by introducing new parameters.

The augmented Lagrangian pattern search (ALPS) has been used to solve nonlinear constraint problems in PS algorithm. ALPS proceeds to solve a nonlinear optimization problem with nonlinear constraints, linear constraints, and bounds [25, 28–30]. The variables bounds and linear constraints are handled separately from nonlinear constraints, in which a sub-problem is constructed and solved (having the objective function and nonlinear constraint function) using the Lagrangian and the penalty factors. Such a sub-problem is minimized using a PS method, where the linear constraints and bounds are satisfied. ALPS starts with an initial value for the penalty parameter, where the PS algorithm minimizes a series of the subproblem, which estimates the original problem. If the required accuracy and feasibility conditions are met, then the Lagrangian estimates are updated. If not, a penalty factor is added to the penalty parameter. This, in turns, leads to a new formation of a subproblem and ultimately results in a new minimization problem. The above steps are repeated until one of the stopping criteria is reached. For further explanation on how PS handles constraints, refer to [25–27, 31].

4. Numerical Results

A set of Matlab files, incorporated in the GA and DS toolbox, implementing the proposed PS method, have been used to solve various ED problems. Thus, cost coefficients of the fuel cost and the combined objective function for all test cases have been coded in Matlab environment.

Initially, several runs have been carried out with different values of the key parameters of PS, such as the initial mesh size and the mesh expansion and contraction factors. In this study, the mesh size and the mesh expansion and contraction factors are selected as 1, 2, and 0.5, respectively. In addition, a vector of initial points, *i.e.*, X_0, was randomly generated (each initial point is bounded within the generators limits) to provide an initial guess for the PS to proceed. As for the stopping criteria, all tolerances were set to 10^{-6}, and the maximum number of iterations and function evaluations set to 1000.

Case I: EDVP

This test case consists of 13 generating units with a quadratic cost function combined with the effects of valve-point loading. The unit's data (upper and lower bounds) along with the cost coefficients for the fuel cost (a, b, c, e, and f) for the 13 generators with valve-point loading are given in [32, 33]. Note that losses are ignored in this case.

The PS algorithm has been executed 50 times with different starting points to study its performance and effectiveness. The solution of the PS method and the execution times for the 50 runs were compared with the outcome of other evolutionary methods applied to the same test system as reported in [33]. This numerical experiment compares the performance of the PS with the other methods in terms of the dispatching costs and convergence speed. Table 1 shows the optimal solutions determined by PS for the 13 generators, while the execution time and cost comparison are shown in Table 2.

As can be seen from Table 2, the optimum solution of the PS is better than the solutions of all the other evolutionary methods. Moreover, the execution time is significantly shorter than for the other methods [33].

The convergence of the PS process is shown in Figure 2, where only 70 iterations were needed to locate the optimal solution. However, PS may be allowed to continue the search in the neighborhood of the optimal solution to increase the confidence in the result. In this case, the PS terminates after 52 further iterations (a total of 122).

Figure 3 illustrates the mesh size throughout the convergence process. It is apparent that the mesh size decreases until the algorithm terminates, in this case at a mesh size

Table 1
Generator loading and fuel cost determined by PS with total load demand of 1800 MW

Generator	Generator production (MW)
Pg_1	538.5587
Pg_2	224.6416
Pg_3	149.8468
Pg_4	109.8666
Pg_5	109.8666
Pg_6	109.8666
Pg_7	109.8666
Pg_8	109.8666
Pg_9	109.8666
Pg_{10}	77.4666
Pg_{11}	40.2166
Pg_{12}	55.0347
Pg_{13}	55.0347
$\sum Pg_i = 1800$ MW	Total cost: $17,969.17

Table 2
Comparison of PS, GA, and EP

Evolution method	Mean time (s)	Best time (s)	Mean cost ($)	Maximum cost ($)	Minimum cost ($)
CEP	294.96	293.41	18,190.32	18,404.04	18,048.21
FEP	168.11	166.43	18,200.79	18,453.82	18,018.00
MFEP	317.12	315.98	18,192.00	18,416.89	18,028.09
IFEP	157.43	156.81	18,127.06	18,267.42	17,994.07
PS	5.88	1.65	18,088.84	18,233.52	17,969.17

CEP: Classical evolutionary programming; FEP: fast evolutionary programming; MFEP: modified fast evolutionary programming; IFEP: improved fast evolutionary programming.

of 1.5259e–005, which is more than the stopping criteria, indicating that this particular run did not terminate on the mesh size tolerance. Figure 3 shows that the polling was initially successful, leading to enlarging the mesh size. At iteration number 8, the mesh size has decreased, indicating an unsuccessful poll in the previous iteration. This scenario continues throughout until reaching one of the termination criteria.

The PS has determined the optimal solution for 50 different initial points. The solutions of each run are shown in Figure 4. The total execution time for the 50 runs

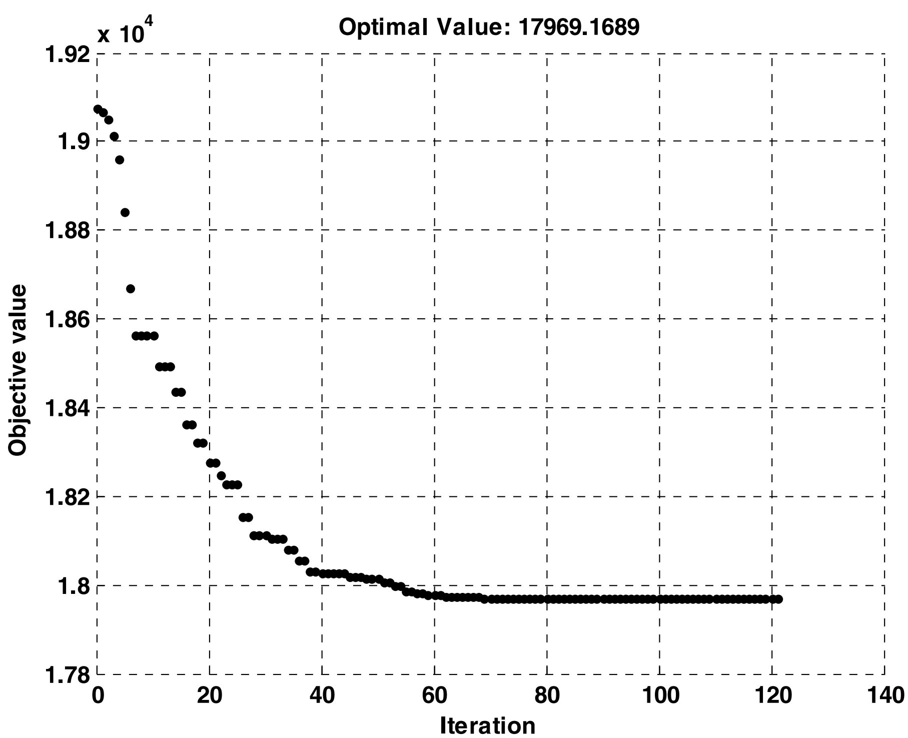

Figure 2. Convergence of PS for the 13 generating units.

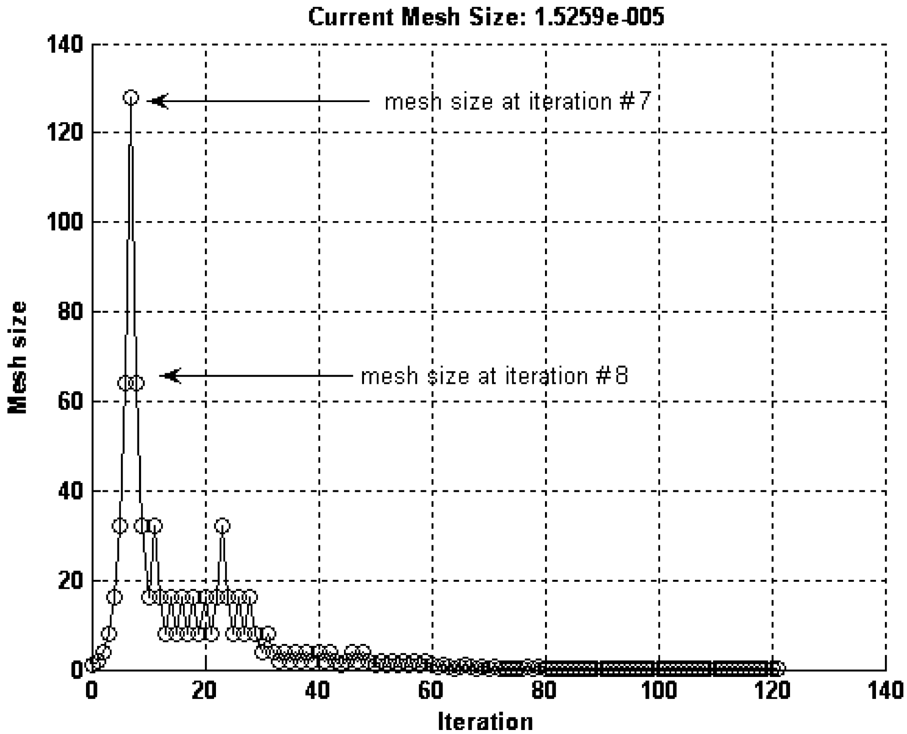

Figure 3. Convergence of PS mesh size for the 13 generating units.

was 294.06 s. For this test case, looking at the maximum, mean, and minimum costs in Table 2, it may be clearly seen that PS outperforms GA and evolutionary programming (EP) by reaching a lower value of the maximum and mean costs for 50 different runs.

Case II: MAED

The MAED problem considered consists of four areas with tie lines connecting these areas. Each area contains four generation units. Note that quadratic cost functions are used to model the cost of generation $F(P_{gi})$, but the tie line transmission costs, $G(t_{jk})$, are assumed to be linear functions of the power transfer. The generators' data and the tie lines' coefficients, along with their limits, are all given in [14].

Different heuristic methods, such as particle swarm optimization (PSO) and EP, have been applied to the same problem, and the results are reported in [34, 35]. The results using the PS and other methods are shown in Tables 3 and 4. The optimal solution obtained by PS is obviously better than those obtained by various EP algorithms and is similar to the result obtained by network flow programming (NFP) [14], which is not heuristic in nature. In addition, the computation time of PS is less than the execution times of the variants of EP.

As illustrated in Figure 5, PS has located the optimal solution after only 200 iterations, but it continues computating and refining the result. Figure 6 shows the mesh size expansion and contraction behavior during the PS search for the global minimum.

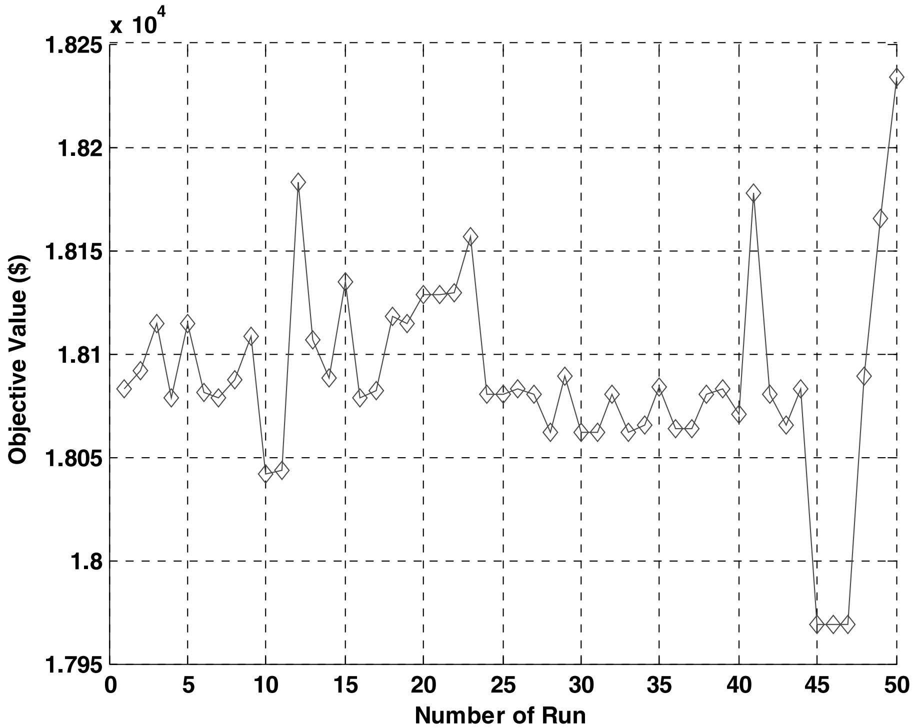

Figure 4. Objective function value for 50 different starting points.

Table 3
Comparison of PS and other heuristic methods (16 generators)

Generator		Optimization techniques				
		IFEP	FEP	CEP	NFP	**PS**
Area 1	P1 (MW)	149.998	149.997	150.000	150.000	**150.000**
Demand	P2 (MW)	099.986	099.968	100.000	100.000	**100.000**
400 MW	P3 (MW)	068.270	067.017	068.826	066.970	**066.971**
	P4 (MW)	099.940	099.774	099.985	100.000	**100.000**
Area 2	P5 (MW)	056.349	057.181	056.373	056.970	**56.9718**
Demand	P6 (MW)	096.753	095.554	093.519	096.250	**96.2518**
200 MW	P7 (MW)	041.264	041.736	042.546	041.870	**41.8718**
	P8 (MW)	072.586	072.748	072.647	072.520	**72.5218**
Area 3	P9 (MW)	050.003	050.030	050.000	050.000	**050.002**
Demand	P10 (MW)	035.985	036.552	036.399	036.270	**036.272**
350 MW	P11 (MW)	038.012	038.413	038.323	038.490	**038.492**
	P12 (MW)	037.426	037.001	036.903	037.320	**037.322**
Area 4	P13 (MW)	149.988	149.986	150.000	150.000	**150.000**
Demand	P14 (MW)	099.964	099.995	100.000	100.000	**100.000**
300 MW	P15 (MW)	057.601	057.568	056.648	057.050	**057.051**
	P16 (MW)	095.874	096.482	095.826	096.270	**096.271**

Table 4
Comparison of PS and other heuristic methods (tie lines)

Area		Tie lines values (MW)				
From	To	IFEP	FEP	CEP	NFP	**PS**
1	2	00.094	00.062	00.000	00.000	**00.000**
1	3	18.649	18.241	19.587	18.180	**18.181**
1	4	00.000	00.000	00.000	00.000	**00.000**
2	1	00.018	00.000	00.018	00.000	**00.000**
2	3	69.997	69.790	68.861	69.730	**69.730**
2	4	00.000	00.000	00.000	00.000	**00.000**
3	1	00.000	00.000	00.000	00.000	**00.000**
3	2	00.000	00.000	00.000	00.000	**00.000**
3	4	00.000	00.000	00.000	00.000	**00.000**
4	1	00.549	01.548	00.758	01.210	**01.210**
4	2	02.951	02.509	01.789	02.110	**02.111**
4	3	99.927	99.974	99.927	100.00	**100.00**
Total cost ($/h)		7337.51	7337.52	7337.75	7337.0	**7336.98**
Computation time (s)		23.97	7.47	7.82/11.49	—	**5.77**
Population size		100	100	100	—	—
No. of iterations		585	645	758/920	—	**1225**

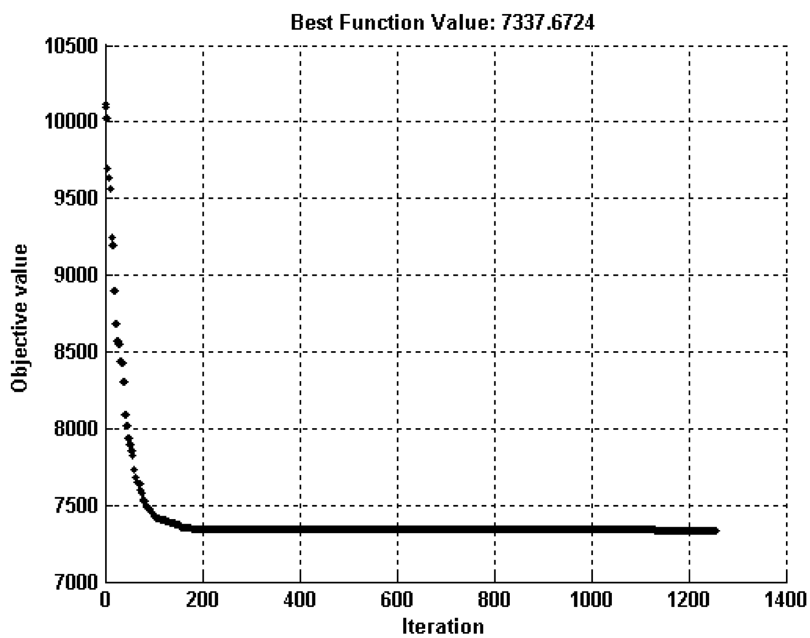

Figure 5. Convergence of PS for MAED.

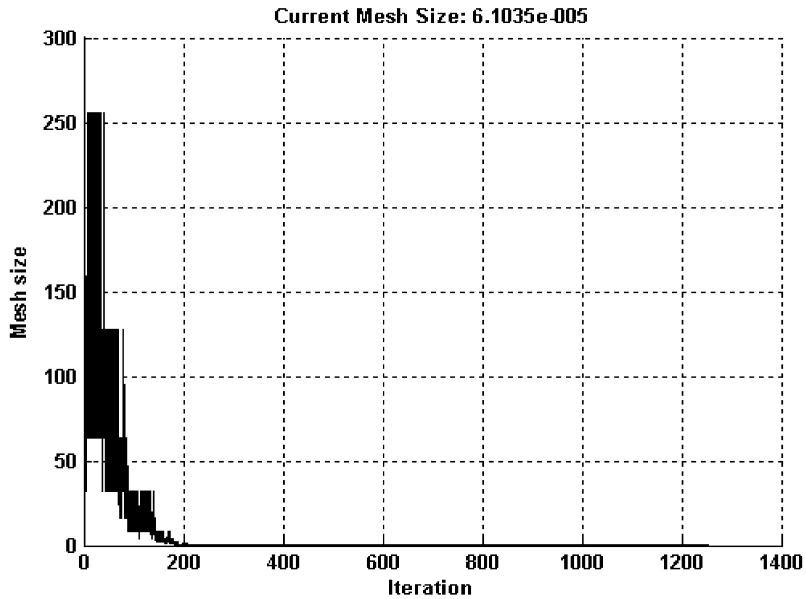

Figure 6. Mesh size.

Case III: CEED

In this combined environmental ED case, a six-generator system is considered. Information about the generators' fuel cost, NO_x emission functions, the B matrix, loss coefficients, and the operating limits are detailed in [36]. The total load demand is set to 700 MW, and the weighting factor is 0.5.

The PS results of the line losses, emission, fuel cost, total cost, and computation time are presented and compared with results of other heuristic methods (GA and EP from [34, 35]) in Table 5. It can be seen that PS has reached the best total and fuel costs, and also has produced the best time of computation compared with the other methods. In addition, PS came third in line losses and emissions. The convergence of the PS needs only 40 iterations and 2.05 s to reach the optimal solution, which are significantly less for EP and GA.

Case IV: QCFED

According to [17], it is an industry practice to adopt a cubic polynomial for modeling fuel costs of generation units. This is particularly important in situations with generation units having non-monotonically increasing incremental curves [19]. In this case, a three-generator system is considered with third-order cost functions. Information about the generators' fuel-cost coefficients, the B matrix, loss coefficients, and the operating limits are detailed in [18].

The optimal solution of PS is given in Table 6, along with the results obtained by conventional DP from [18] for comparison purposes. Clearly, the PS has converged to a better solution, while the execution time is less than 1 s. Also, the significant reduction in line losses is obvious.

Table 5
Comparison of PS and other heuristic methods

	Optimization techniques				
Generator	IFEP	FEP	CEP	FCGA	**PS**
P1 (MW)	077.142	077.358	077.274	080.16	**77.4318**
P2 (MW)	049.925	049.669	049.639	053.71	**048.894**
P3 (MW)	048.764	048.316	048.535	040.93	**048.516**
P4 (MW)	103.486	104.369	103.525	116.23	**104.5679**
P5 (MW)	259.805	260.663	260.695	251.20	**260.8632**
P6 (MW)	191.828	190.473	191.233	190.62	**190.6723**
Line losses (MW)	30.949	30.849	30.901	32.850	**30.945**
Emission (kg/h)	530.5164	532.5046	524.49	527.46	**528.33**
Fuel cost ($/h)	38,214.02	38,214.23	38,216.47	38,408.82	**38,208.63**
Total cost ($/h)	19,369.84	19,369.89	19,369.84	19,468.14	**19,368.48**
Computation time (s)	3.874	1.598	4.48	—	**2.05**
No. of iterations	57	65	77	—	**40**

FCGA: Fuzzy controlled genetic algorithm.

Table 6
Comparison of PS and DP with total demand 1400 MW

	Optimization technique	
Generator	DP	**PS**
P1 (MW)	360.2	**372.29**
P2 (MW)	406.4	**356.0**
P3 (MW)	676.8	**712.0**
Line losses (MW)	43.4	**40.29**
Fuel cost ($/h)	6642.26	**6639.01**
Computation time (s)	—	**0.619**
No. of iterations	5	**6**

5. Conclusions

This paper introduces a new approach based on PS optimization to solve various problems of power system ELD. The proposed method has been applied to four types of problems, including the EDVP effects, MAED, CEED, and QCFED. Through extensive comparisons, it has been demonstrated that the PS approach outperforms other heuristic methods in terms of reaching a better optimal solution; at the same time, the simplicity of the PS process makes the algorithm computationally more efficient. However, the PS is more sensitive than the GA or EP to the initial guess (starting point) and appears to rely more heavily on how close the given initial point is to the expected optimum. This, in turn, makes the PS method more susceptible to getting trapped in local minima. Overall, the PS approach has been found to be a very efficient technique to study a wide range of optimization problem in the area of power system.

Acknowledgment

This work has been supported by the government of The State of Kuwait, Public Authority of Applied Science & Training, Kuwait (Project # TS-06-02).

References

1. Adler, R. B., and Fischl, R., "Security constrained economic dispatch with participation factors based on worst case bus load variations," *IEEE Transactions on: Power Apparatus and Systems*, Vol. 96, pp. 347–356, 1977.
2. Bui, R. T., and Ghaderpanah, S., "Real power rescheduling and security assessment," *IEEE Trans. Power Apparatus Syst.*, Vol. PAS-101, pp. 2906–2915, 1982.
3. Pancholi, R. K., and Swarup, K. S., "Particle swarm optimization for security constrained economic dispatch," *International Conference on Intelligent Sensing and Information Processing*, Chennai, India, pp. 7–12, 2004.
4. El-Sharkawy, M., and Nieebur, D., "Artificial neural networks with application to power systems," *IEEE Power Engineering Society, A Tutorial Course*, 1996.
5. Yalcinoz, T., and Short, M. J., "Neural networks approach for solving economic dispatch problem with transmission capacity constraints," *IEEE Trans. Power Syst.*, Vol. 13, pp. 307–313, 1998.
6. Youssef, H. K., and El-Naggar, K. M., "Genetic based algorithm for security constrained power system economic dispatch," *Elec. Power Syst. Res.*, Vol. 53, pp. 47–51, 2000.
7. Chen, C. L., and Chen, N., "Direct search method for solving economic dispatch problem considering transmission capacity constraints," *IEEE Trans. Power Syst.*, Vol. 16, pp. 764–769, 2001.
8. Hooke, R., and Jeeves, T. A., "Direct search solution of numerical and statistical problems," *J. Assoc. Computing Mach.*, Vol. 8, pp. 212–229, 1961.
9. Lewis, R. M., Torczon, V., and Trosset, M. W., "Direct search methods: Then and now," *J. Computat. Appl. Math.*, Vol. 124, pp. 191–207, 2000.
10. Deb, K., *Optimization for Engineering Design: Algorithms and Examples*, New Delhi: Prentice Hall, 1995.
11. Walters, D. C., and Sheble, G. B., "Genetic algorithm solution of economic dispatch with valve point loading," *IEEE Trans. Power Syst.*, Vol. 8, pp. 1325–1332, 1993.
12. Victoire, T. A. A., and Jeyakumar, A. E., "Hybrid PSO-SQP for economic dispatch with valve-point effect," *Elec. Power Syst. Res.*, Vol. 71, pp. 51–59, 2004.
13. Victoire, T. A. A., and Jeyakumar, A. E., "A modified hybrid EP-SQP approach for dynamic dispatch with valve-point effect," *Int. J. Elec. Power Energy Syst.*, Vol. 27, pp. 594–601, 2005.
14. Streiffert, D., "Multi-area economic dispatch with tie line constraints," *IEEE Trans. Power Syst.*, Vol. 10, pp. 1946–1951, 1995.
15. Farag, A., Al-Baiyat, S., and Cheng, T. C., "Economic load dispatch multiobjective optimization procedures using linear programming techniques," *IEEE Trans. Power Syst.*, Vol. 10, pp. 731–738, 1995.
16. Song, Y. H., Wang, G. S., Wang, P. Y., and Johns, A. T., "Environmental/economic dispatch using fuzzy logic controlled genetic algorithms," *IEE Proc. Generat. Transm. Distribut.*, Vol. 144, pp. 377–382, 1997.
17. Liang, Z. X., and Glover, J. D., "Improved cost functions for economic dispatch compensations," *IEEE Trans. Power Syst.*, Vol. 6, pp. 821–829, 1991.
18. Liang, Z. X., and Glover, J. D., "A zoom feature for a dynamic programming solution to economic dispatch including transmission losses," *IEEE Trans. Power Syst.*, Vol. 7, pp. 544–550, 1992.
19. Jiang, A., and Ertem, S., "Economic dispatch with non-monotonically increasing incremental cost units and transmission system losses," *IEEE Trans. Power Syst.*, Vol. 10, pp. 891–897, 1995.

20. Saadat, H., *Power System Analysis*, Boston, MA/London: WCB/McGraw-Hill, 1999.
21. Grainger, J. J., and Stevenson, W. D., *Power System Analysis*, New York: McGraw-Hill, 1994.
22. Goldberg, D. E., *Genetic Algorithms in Search, Optimization, and Machine Learning*, Reading, MA: Addison-Wesley, 1989.
23. Michalewicz, Z., *Genetic Algorithms + Data Structures = Evolution Programs*, 3rd rev. and extended ed., New York: Springer-Verlag, 1996.
24. Youssef, H. K., El-Shibini, M., and Hazaa, G. A., "Some new aspects in power system dynamic security using pattern recognition," *Second Middle East Power Conference (MEPCON-92)*, pp. 308–313, Egypt, January 1992.
25. Lewis, R. M., and Torczon, V., "A globally convergent augmented Lagrangian pattern search algorithm for optimization with general constraints and simple bounds," *SIAM J. Optim.*, Vol. 12, pp. 1075–1089, 2001.
26. Conn, A. R., Gould, N. I. M., and Toint, P. L., "A globally convergent augmented Lagrangian algorithm for optimization with general constraints and simple bounds," *SIAM J. Numer. Anal.*, Vol. 28, pp. 545–572, April 1991.
27. Conn, A. R., Gould, N. I. M., and Toint, P. L., "A globally convergent augmented Lagrangian pattern search algorithm for optimization with general constraints and simple bounds," *Math. Comput.*, Vol. 66, pp. 261–288, 1997.
28. Lewis, R. M., and Torczon, V., "Pattern search algorithms for linearly constrained minimization," *SIAM J. Optim.*, Vol. 10, pp. 917–941, 1999.
29. Lewis, R. M., and Torczon, V., "Pattern search algorithms for bound constrained minimization," *SIAM J. Optim.*, Vol. 9, pp. 1082–1099, 1999.
30. Torczon, V., "On the convergence of pattern search algorithms," *SIAM J. Optim.*, Vol. 7, pp. 1–25, 1997.
31. The Math Works Inc., *Genetic Algorithm and Direct Search Toolbox for Use with Matlab User's Guide*, 2nd ed.
32. Wong, K. P., and Wong, Y. W., "Thermal generator scheduling using hybrid genetic simulated-annealing," *IEE Proc. Generat. Transm. Distrib.*, Vol. 142, pp. 372–380, July 1995.
33. Sinha, N., Chakrabarti, R., and Chattopadhyay, P. K., "Evolutionary programming techniques for economic load dispatch," *IEEE Trans. Evolut. Comput.*, Vol. 7, pp. 83–94, 2003.
34. Jayabarathi, T., Jayaprakash, K., Jeyakumar, D. N., and Raghunathan, T., "Evolutionary programming techniques for different kinds of economic dispatch problems," *Elec. Power Syst. Res.*, Vol. 73, pp. 169–176, 2005.
35. Jeyakumar, D. N., Jayabarathi, T., and Raghunathan, T., "Particle swarm optimization for various types of economic dispatch problems," *Int. J. Elec. Power Energy Syst.*, Vol. 28, pp. 36–42, 2006.
36. Dhillon, J. S., Parti, S. C., and Kothari, D. P., "Stochastic economic emission load dispatch," *Elec. Power Syst. Res.*, Vol. 26, pp. 179–186, 1993.