A HYBRID GA–PS METHOD TO SOLVE THE ECONOMIC LOAD DISPATCH PROBLEM

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ABSTRACT

This study presents a new approach based on a hybrid algorithm consisting of Genetic Algorithm (GA) and Pattern Search (PS) techniques for solving the economic load dispatch (ELD) problem. The objective is to minimize the nonlinear function, which is the total fuel cost of thermal generating units, subject to the usual constraints. The proposed method hybrid GA–PS algorithm has been examined and tested for standard IEEE 30 bus system. The hybrid GA–PS method is demonstrated and compared with conventional OPF method and the intelligence heuristic algorithm such as genetic algorithm, evolutionary programming. From simulation results, it has been found that hybrid GA–PS algorithm method is highly competitive for its better general convergence performance.

Keywords: *Economic dispatch; Direct Search method; Pattern Search method (PS); Genetic Algorithms (GA); Load Flow.*

1. INTRODUCTION

In power system operation, the economic dispatch (ED) problem is an important optimization problem. Moreover, it has complex and nonlinear characteristics with heavy equality and inequality constraints. Generally, there are two types of ED problem, i.e. static and dynamic. Solving the static ED problem is subject to the power balance constraints and generator operating limits. For the dynamic ED, it is an extension of the static ED problem. The dynamic ED takes the ramp rate limits and prohibited operating zone of the generating units into consideration [1].

The methods for solving this kind of problem include traditional operational research algorithms and modern heuristic methods. Some of these methods are successful in locating the optimal solution, but they are usually slow in convergence and require heavy computational cost. Some other methods may risk being trapped to a local optimum, which is the problem of premature convergence [2].

Finally, a particular family of global optimization methods, known as Direct Search methods, originally introduced and developed by researchers in 1960s [3], has recently received some attention. The Direct Search methods are simply structured to explore a set of points, in the vicinity of the current position, looking for a smaller objective function value than the current one. This family includes Pattern Search (PS) algorithms, Simplex Methods (SM), Powell Optimization (PO) and others [4]. Direct Search methods, in contrast to more standard optimization methods, are often called derivative-free as they do not require any information about the gradient (or higher derivative) of the objective function when searching for an optimal solution. Therefore Direct Search methods are particularly appropriate for solving non-continuous, non-differentiable and multimodal (i.e. multiple local optima) optimization problems, such as the economic dispatch [5, 6].

The main objective of this study is to introduce a hybrid method that combines the Genetic Algorithm (GA) and Pattern Search (PS) – referred to as the hybrid GA–PS method – in the context of power system economic dispatch problem [7]. The proposed hybrid method has eliminated the need to provide a suitable starting point for PS [8]. This feature led to the reduction of total execution time of the algorithm when compared to other reported methods. In this paper, a the hybrid GA–PS method is presented and used to solve the ELD problem under some equality and inequality constraints. An application was performed on the IEEE 30 bus – 6 generators test system. Simulation results confirm the advantage of computation rapidity and solution accuracy.

The feasibility of the proposed method is to demonstrated and compared to those reported in the literature. The results are promising and show the effectiveness of the proposed method.

2. FORMULATION OF THE ECONOMIC PROBLEM

The total cost of operation of generators includes fuel, and maintenance cost but for simplicity only variable costs need to consider are fuel costs. The fuel cost is Important for thermal power plant. For the fuel costs, it is assumed that fuel cost curves for each generating unit is given [9].

Consider a system with n generators committed and that all the loads P_D, find P_{Gi} and V_i, P_L, δ_i. $i=1,2,..,n$. To minimize the total fuel cost

$$F=\sum_{i=1}^{N} C_i\,(P_{Gi}) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \qquad (1)$$

Where N is the total number of generation units, a_i, b_i, c_i is the cost coefficients of generating unit and PGi is the real power generation of i_{th} unit. $i = 1, 2 \ldots$ to N.

Subject to the satisfaction of the power flow equations and the following inequality constraints on generator power, voltage magnitude and line power flow.

2.1 Equality Constraints As :

$$P_{gi} - P_{di} - \sum_{j=1}^{N} |Vi||Vj||Yji|\cos(\delta i - \delta j - \theta ij) = 0$$

and (2)

$$Q_{gi} - Q_{di} - \sum_{j=1}^{N} |Vi||Vj||Yji|\sin(\delta i - \delta j - \theta ij) = 0$$

$$\sum P_{gi} - P_D - P_L = 0$$

Where P_D is the demand power and P_L is the power loss.

2.2 Inequality Constraints As:

Branch flow limits:

$$|Si| \le S_i^{\max} \qquad i = 1,\ldots nl \qquad (3)$$

Where n_l is the number of lines.

Voltage at load buses

$$|S_D|^{\min} \le |Si| \le |S_D|^{\max} \qquad i = 1,\ldots nd \qquad (4)$$

Where n_d is the number of load buses.

Generator MVAR

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad i = 1,\ldots N \qquad (5)$$

Slack bus MW

$$P_G^{\min} \le P_G \le P_G^{\max} \qquad (6)$$

Transformer tap setting

$$t_k^{\min} \le t_k \le t_k^{\max} \qquad (7)$$

Upper and lower bounds with bus voltage phase angles:

$$\delta_i^{\min} \le \delta_i \le \delta_i^{\max} \qquad (8)$$

Brief explanation on the problem formulation id given below [9].

1. The power flow or load flow equations must be satisfied. They are equality constraint in the optimization process.
2. The lower limit on P_{Gi} due to boiler and / or other thermodynamic considerations and upper limits is set by thermal limits on the turbine generator unit.
3. The voltage constraint will keep the system voltages near their rated or nominal values. The voltage should be neither too high nor low and the objective is to help maintain the consumer's voltage
4. Constraints on transmission line powers relate to stability and thermal units.

3. PATTERN SEARCH OPTIMIZATION METHOD

Due to the limitations on the length of this paper, and good coverage of the GA and SQP techniques in the literature, only the PS method will be briefly mentioned here. The Pattern Search (PS) is an evolutionary routine suitable for solving a variety of optimization problems that lie outside the scope of typical optimization tasks, and has the advantage of being very simple in concept, easy to implement and computationally efficient. Unlike, say, genetic algorithms [10, 11], the PS has a flexible and well-balanced operator able to enhance and adapt the global as well as fine tune the local search. A helpful review of direct search methods for unconstrained optimization may be found in [4].

The Pattern Search (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, and easy to implement and computationally efficient algorithm. Unlike other heuristic algorithms, such as GA, PS possesses a flexible and well-balanced operator to enhance and adapt the global and fine tune local search. A historic discussion of direct search methods for unconstrained optimization is presented in reference [12]. The authors gave a modern prospective on the classical family of derivative-free algorithms, focusing on the development of direct search methods.

The Pattern Search (PS), algorithm proceeds by computing a sequence of points that may or may not approaches to the optimal point. The algorithm starts by establishing a set of points called 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 maybe better explained by the following:

First: The Pattern search 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 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 Pattern search algorithm adds the direction vectors to the initial point X_0 to compute the following mesh points:

X_0 + [0 1], X_0 + [1 0], X_0 + [-1 0] and X_0 + [0 -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 point, then the poll is successful and the algorithm sets this point equal to X1 [12].

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.

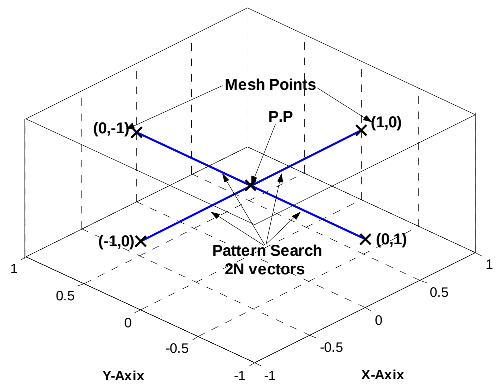

Fig. 1 : 2N Pattern Vectors which forms the mesh points

Second: Now if iteration 3, (mesh size= 4), ends up being unsuccessful poll, i.e. none of the mesh points has a smaller objective function value than the value at X_2 , so the poll is called an unsuccessful poll. In this case, the algorithm does not change the current point at the next iteration. That 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 [12].

The Pattern search 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 [4, 12]:

The mesh size is less than mesh tolerance.

The number of iterations performed by the algorithm reaches the value of max iteration.

The total number of objective function evaluations performed by the algorithm reaches the value of Max function evaluations. The distance between the point found at one successful poll and the point found at the next successful poll is less than X tolerance.

The change in the objective function from one successful poll to the next successful poll is less than function tolerance.

All the parameters involved in the Pattern search optimization algorithm can be pre-defined subject to the nature of the problem being solved.

The above steps and how PS evolves are depicted by the flow chart of Fig. 2. It should be noted that all the parameters involved in the pattern search optimization algorithm can be pre-defined subject to the nature of the problem being solved [13].

The PS operator gives the user a great deal of control regarding the direction of the search. After conducting a large number of experiments for many values of expansion and contraction factor, the best combination was found to be 2 and 0.5 respectively, giving an average best performance of optimal speed of computation as well as the right direction of the search [13].

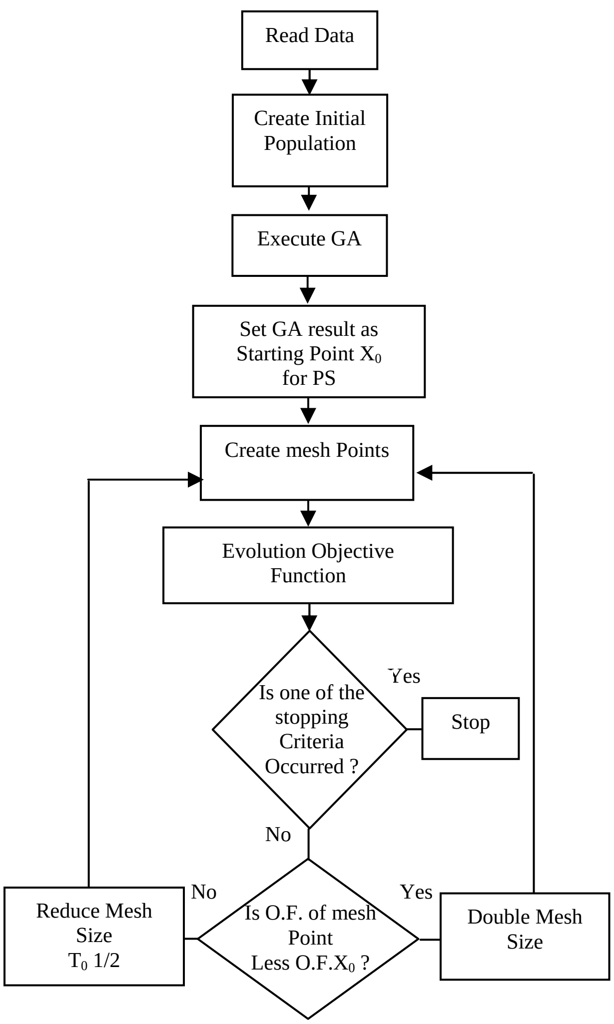

Fig. 2 : Flow chart of pattern search [13].

4. SIMULATION RESULTS AND DISCUSSION

The program has been developed and executed under Matlab system. The program was written and executed on Pentium 4 having 2.4 GHZ 1GB DDR RAM.

The proposed GA-PS algorithm is tested on standard on The standard IEEE 30 bus system consists of 6 thermal units (Tables A.1), 24 load buses and 41 transmission lines of which four of the branches (6-9), (6-10), (4-12) and (28-27) are with the tap setting transformer. The total system demand is 283.4 MW [14].

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 factor are selected as 1, 2 and 0.5, respectively. In addition, a vector of initial points, i.e. X_0, was randomly generated to provide an initial guess for the PS to proceed. As for the stopping criteria, all tolerances were set to 10-6 maximum number of iterations and function evaluations were set to 50 [8].

4.1 Case I: PS method (without GA)

In this case applied PS techniques for solving the economic load dispatch problem. The obtained results using PS based OPF are given in Tables 1.

Fig. 3. shows the cost convergence of PS based OPF algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 50 generations. Hence it is clears from the Fig. That the solution is converged to a high quality solution at the early iterations (25 iterations).

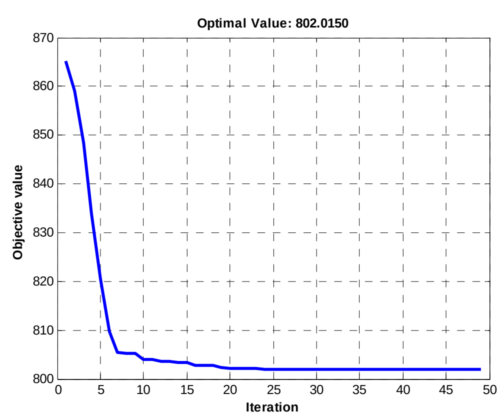

Fig. 3 : Convergence of PS for the IEEE 30 bus system.

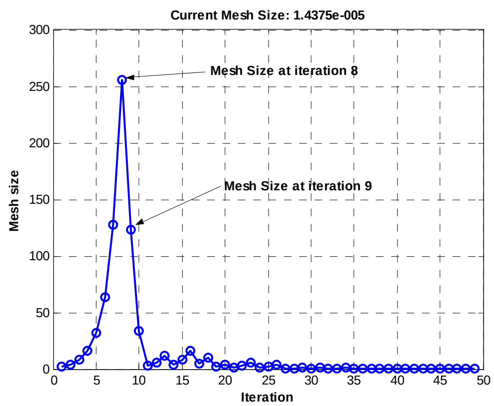

Fig. 4 : Convergence of PS mesh size for the IEEE 30 bus system (case I).

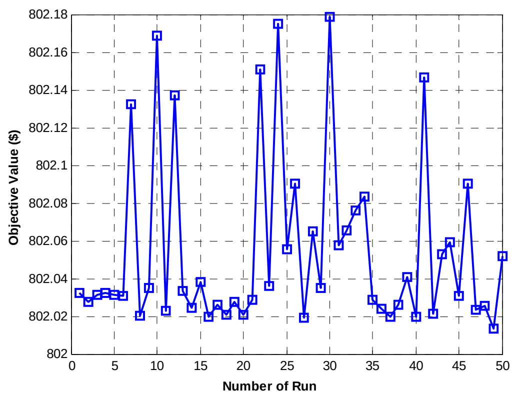

Fig. 5 : Objective function value for 50 different starting point (case I).

The minimize cost and power loss obtained by the proposed algorithm is less than value reported in [4, 15, 16].

Table1 : Comparison of the PS-OPF with different evolutionary methods of optimization viewpoint cost, losses and times of convergence

	IEP [4]	EP-OPF [15]	SADE_ALM [16]	**PS**
Pg1 [MW]	176.2358	173.8262	176.1522	**175.7276**
Pg2 [MW]	49.0093	49.998	48.8391	**48.6812**
Pg5 [MW]	21.5023	21.386	21.5144	**21.4282**
Pg8 [MW]	21.8115	22.63	22.1299	**22.8313**
Pg11 [MW]	12.3387	12.928	12.2435	**12.0667**
Pg13 [MW]	12.0129	12.00	12.0000	**12.0000**
Power Loss [MW]	9.5105	9.3683	9.4791	**9.3349**
Generation cost [$/hr]	802.465	802.5557	802.404	**802.0150**

The convergence of optimal solution using PS is shown in Fig. 3, where only about 25 iterations were needed to find the optimal solution. However, PS may be allowed to continue the search in the neighborhood of the optimal point to increase the confidence in the result. PS stops after 50 more iteration and returns the optimal value.

Fig. 4 depicts the mesh size throughout the convergence process. It is apparent form the figure that the mesh size decreases until the algorithm terminates, in this case at mesh size 1.4375e-005 which is more that the giving as stopping criteria, thus indicating that this particular run did not terminate using the mesh size tolerance [17, 16]. Fig. 7 shows that for the first 8 iteration the poll was successful since the mesh size keeps increasing as the algorithm had to expand the scope of the search. This is accomplished by multiplying the current mesh size by the expansion factor, in this study taken as 2. This scenario continued until iteration number 8 when the mesh size reached 256. At iteration number 9 the mesh size decreased by half due to multiplying the current mesh size by the contracting factor, indicating an unsuccessful poll in the previous iteration. This process continues until reaching one of the termination criteria [16].

It is worth mentioning that the mean and the maximum costs are higher than those of the other methods, and this is a certain drawback of the performance of PS in this test. Moreover, it has been observed that the algorithm is quite sensitive to the initial (starting) point and how far it is from the global optimal solution [18, 8]. Fig. 5 illustrates the sensitivity of PS where a hundred solutions were obtained by PS with different initial values. The optimal solution has been reached a number of times for initial points around run number 49.

4.2 Case II: GA-PS method

In this case applied the hybrid GA–PS algorithm techniques for solving the economic load dispatch (ELD) problem to standard IEEE 30 bus system.

The obtained results using hybrid GA–PS algorithm OPF are given in Tables 2.

If the parameters of GA : the number of generation is 100 iterations and population size is 30 individus with probability of crossover P_c = 0.9 and mutation P_m = 0.03.

Fig. 6. shows the cost convergence of hybrid GA–PS algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 50 generations. Hence it is clears from the Fig. That

the solution is converged to a high quality solution at the early iterations (25 iterations).

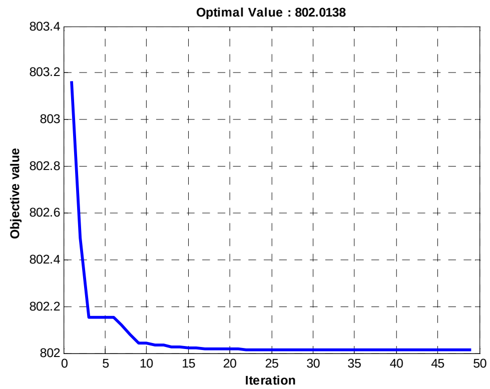

Fig. 6 : Convergence of PS for the IEEE 30 bus system.

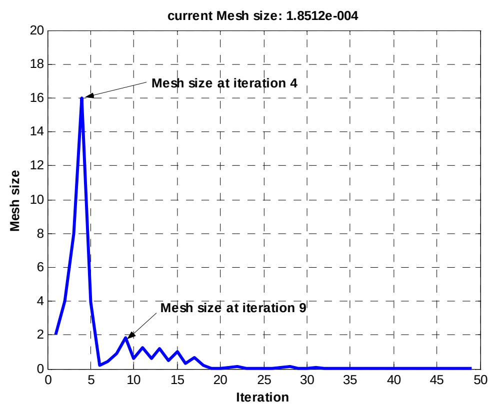

Fig. 7 : Convergence of PS mesh size for the IEEE 30 bus system (case II).

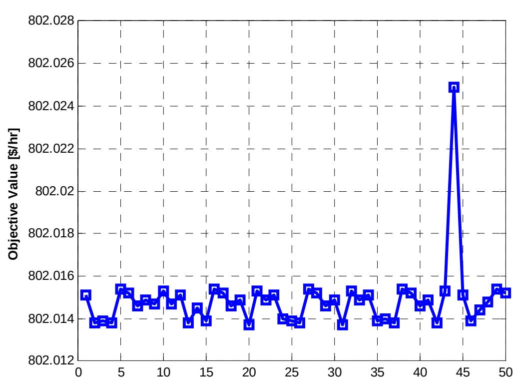

Fig. 8 : Objective function value for 50 different starting point (case II).

The minimize cost and power loss obtained by the proposed algorithm is less than value reported in [5, 15, 16].

Table 2 : Comparison of the GA-PS with different evolutionary methods of optimization viewpoint cost, losses and times of convergence

	IEP [5]	EP-OPF [15]	SADE_ALM [16]	PS	GA-PS
Pg1 [MW]	176.235	173.8262	176.1522	175.727	**75.6627**
Pg2 [MW]	49.0093	49.998	48.8391	48.6812	**48.6413**
Pg5[MW]	21.5023	21.386	21.5144	21.4282	**21.4222**
Pg8 [MW]	21.8115	22.63	22.1299	22.8313	**22.6219**
Pg11 [MW]	12.3387	12.928	12.2435	12.0667	**12.3806**
Pg13 [MW]	12.0129	12.00	12.0000	12.0000	**12.0000**
Power Loss [MW]	9.5105	9.3683	9.4791	9.3349	**9.3286**
Generation cost [$/hr]	802.465	802.5557	802.404	802.0150	**802.0138**

5. CONCLUSIONS

This paper describes a novel hybrid approach based on a combination of Genetic Algorithm (GA) and Pattern Search (PS) to study power system economic dispatch problems. Tow test cases (PS and GA-PS) have been studied and comparisons of the quality of the solution and performance have been conducted against Evolutionary Programming (IEP), (EP-OPF), and hybrid Self-adaptive Differential Evolution methods (SADE_ALM). The results demonstrate that the proposed scheme outperforms the other methods in terms of better optimal solutions.

The GA–PS technique has overcome an important drawback of the PS methods that is the need to supply a suitable starting point. This shortcoming of the PS methods was highlighted in the previous work of the authors as it makes any optimization method relying on a good choice of the initial point possibly more susceptible to getting trapped in local minima, although the much improved speed of computation allows for additional searches to be made to increase the confidence in the solution.

The hybrid GA–PS algorithm, on the other hand, does not require the user to specify the starting point as it is generated automatically for the PS stage by the initial GA phase. Moreover, the performance of the proposed hybrid method improves with the increase of size and complexity of the system. Overall, the proposed algorithm has been shown to perform extremely well for solving economic dispatch problems.

APPENDIX

Table A.1. Generators Data of the IEEE 30 Bus Test System

Bus No.	1	2	5	8	11	13
a [$/h]	0	0	0	0	0	0
b [$/MWh]	2.00	1.75	1.00	3.25	3.00	3.00
C [$/MW^{2}h]	0.00375	0.017	0.0625	0.00834	0.025	0.025
Pgmin (MW)	50	20	15	10	10	12
Pgmax (MW)	200	80	50	35	30	40

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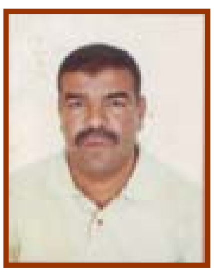

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