Hybrid Genetic Approach for Economic Dispatch with Valve-Point Effect

Mohamed.I.Mahrous ¹  Mohamed.G.Ashmawy ²
¹ Faculty of Engineering, Al-Azhar University, Egypt.
² Elec.Power and Machs.Dep., El-Shorouk Academy, Egypt.

Abstract— Hybrid genetic algorithm (HGA) is proposed in this paper to determine the economic scheduling of electric power generation over a fixed time period under various system and operational constraints. The proposed technique can outperform conventional genetic algorithms (CGAs) in the sense that HGA make it possible to improve both the quality of the solution and reduce the computing expenses. In contrast, any carefully designed GA is only able to balance the exploration and the exploitation of the search effort, which means that an increase in the accuracy of a solution can only occur at the sacrifice of convergent speed, and vice versa. It is unlikely that both of them can be improved simultaneously. The proposed hybrid scheme is developed in such a way that a simple GA is acting as a base level search, which makes a quick decision to direct the search towards the optimal region, and a local search method (pattern search technique) is next employed to do the fine tuning. The aim of the strategy is to achieve the cost reduction within a reasonable computing time. The effectiveness of the proposed hybrid technique is verified on two real public electricity supply systems with 13 and 40 generator units respectively. The simulation results obtained with the HGA for the two real systems are very encouraging with regard to the computational expenses and the cost reduction of power generation.

Keywords — Genetic algorithms, Economic dispatch, Pattern search.

I. INTRODUCTION

Economic dispatch is one of the most important problems to be solved in the operation of a power system. Improvements in scheduling the unit outputs can lead to significant cost savings. The primary objective of the economic dispatch problem (EDP) of electric power generation is to schedule the committed generating unit outputs so as to meet the required load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints [1,2]. This makes the EDP a large-scale highly non-linear constrained optimization problem.

The input–output characteristics of large units are inherently highly non-linear because of valve-point loadings, generating unit ramp rate limits, etc. Furthermore they may generate multiple local minimum points in the cost function. In light of the non-linear characteristics of the units, there is a demand for techniques that do not have restrictions on the shape of the fuel-cost curves. To obtain accurate dispatch results, approaches without restriction on the shape of incremental fuel-cost functions are needed.

Whereas both lambda-iterative and gradient technique methods in conventional approaches to the problems are calculus-based techniques, and require a smooth and convex cost function and strict continuity of the search space. Dynamic programming (DP) [3,4] imposes no restrictions on the nature of the cost curves and therefore it can solve EDP with inherently nonlinear and discontinuous cost curves. This method, however, suffers from the “curse of dimensionality” or local optimality [3, 4].

GA is a stochastic optimization technique, which is based on the principle of natural selection and genetics [5, 6, 7, and 8]. It combines solution evaluation with randomized, structured exchanges of genetic information between solutions to obtain optimality. Also it searches multiple solutions simultaneously in contrast to conventional optimal algorithms. Therefore, the possibility of finding global optimal solution is increased. The main advantage of GA is that it finds near optimal solution in relatively short time compared with other random searching methods.

In recent years, the interest in these algorithms has been rising fast, for that they provide robust and powerful adaptive search mechanisms [9, 10]. GA has an immense potential for applications in the field of power systems and it has been successfully applied to solve various problems in electric power systems such as economic dispatch [11,12,13], unit commitment, reactive power control, hydrothermal scheduling [9,10], and distribution system planning, etc. When compared with the foregoing conventional techniques, GA is well appreciated for their global optimality in complex search space (multiple local optima, multi-objective, non-linear, discontinuous and highly constrained space). Despite the aforementioned success, GA is only capable of identifying the high performance region at an affordable time and displays inherent difficulties in performing local search for numerical applications [14].

To overcome premature convergence and speed up the search process, a hybrid method that integrates the GA with a pattern search algorithm called PS is proposed to take advantage of both GA and the local search techniques. GA is capable of exploring a large space, yet slow in fine tuning local search. In contrast PS techniques [15, 23] can climb hills rapidly; however, they are blind to the potential hills in the neighborhood area and sensitive to the initial starting points. The hybrid GA uses a GA to identify the potential hill within a reasonably short period of time, while PS technique subsequently takes over and rapidly climbs the remaining hill. Therefore, this algorithm increases the possibility of finding global optimal point and improves the convergence speed.

The proposed hybrid technique uses GA as a base level search towards the optimal region and PS method as optimization to do the fine tuning.
Therefore a hybrid function is an optimization function that runs after the genetic algorithm terminates in order to improve the value of the fitness function. The hybrid function uses the final point from the genetic algorithm as its initial point. In this way, the performance of the hybrid method is improved. At the same time, to improve rationality of the distribution of initial population, the hybrid technique integrating the uniform design with the genetic algorithm is proposed.

In order to validate the performance of the proposed HGA, two economic dispatch problems with incremental fuel-cost functions taking into account the valve-point loading effects were tested and the results obtained were compared with those reported in literatures [1, 2, and 16].

II. EDP FORMULATION

The classic EDP minimizes the following incremental fuel-cost function associated to dispatch-able units:

$$\min F = \min \left\{ \sum_{i=1}^{N_p} F_i(P_i) \right\}$$

(1)

Where $F_i(P_i)$ is the fuel-cost function of the $i^{th}$ unit and $P_i$ is the power generated by the $i^{th}$ unit, $P_i$ subject to power balance constraints:

$$\sum_{i=1}^{N_p} P_i = P_D + P_{loss}$$

(2)

Where $P_D$ is the system load demand and $P_{loss}$ is the transmission loss, and generating capacity constraints:

$$P_{min} \leq P_i \leq P_{max}$$

(3)

Where $P_{min}$ and $P_{max}$ are the minimum and maximum power outputs of the $i^{th}$ unit.

The inclusion of valve-point loading effects makes the modeling of the incremental fuel-cost function of the generators more practical. This increases the non-linearity as well as number of local optima in the solution space. Also the solution procedure can easily trap in the local optima in the vicinity of optimal value. The incremental fuel-cost function of the generating units with valve-point loadings is represented as follows [15, 17]:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + e_i \sin\left(f_i(P_{i min} - P_i)\right)$$

(4)

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

The economic dispatch of generation of real power of the generating units is to be done to the required load demand by satisfying the above constraints. The incremental fuel-cost function can be modeled in a more practical fashion by including the valve-point effects [18].

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, thereby the number of local optima is increased. Hence, a technique that overcomes these complexities has to be evolved.

III. HYBRID GENETIC ALGORITHM

III-1 Genetic algorithm [23]

The parameters applied in genetic algorithms are:

- PopulationType: 'doublevector'
- PopInitRange: [2*1 double]
- PopulationSize: 20
- EliteCount: 2
- CrossoverFraction: 0.8000
- MigrationDirection: 'forward'
- MigrationInterval: 20
- MigrationFraction: 0.2000
- Generations: 100
- TimeLimit: Inf
- FitnessLimit: -Inf
- StallLimitG: 50
- StallLimitS: 20
- CreationFcn: uniform
- FitnessScalingFcn: rank
- SelectionFcn: stochastic
- CrossoverFcn: scattered
- MutationFcn: gaussian
- HybridFcn: [patternsearch]

III-2 Pattern search [23]

Direct search is a method for solving optimization problems that does not require any information about the gradient of the objective function. As opposed to more traditional optimization methods that use information about the gradient or higher derivatives to search for an optimal point, a direct search algorithm searches a set of points around the current point, looking for one where the value of the objective function is lower than the value at the current point. You can use direct search to solve problems for which the objective function is not differentiable, or even continuous.

The direct search implements a special class of direct search algorithms called pattern search algorithms [23]. A pattern search algorithm computes a sequence of points that get closer and closer to the optimal point. At each step, the algorithm searches a set of points, called a mesh, around the current point, the point computed at the previous step of the algorithm. The algorithm forms the mesh by adding the current point in the mesh that improves the objective function at the current point; the new point becomes the current point at the next step of the algorithm.

The parameters applied to pattern search are:

- TolMesh: 1.000e-06
- TolX: 1.000e-06
- TolFun: 1.000e-06
- TolBind: 1.000e-03
- MaxIteration: '100*numberofvariables'
- MaxFunEvals: '2000*numberofvariables'
- MeshContraction: 0.5000
- MeshExpansion: 2
- MeshRotate: 'on'
IV. SOLUTION METHODOLOGY

The proposed HGA for EDP with valve-point effects can be summarized as follows:

Step 1: Get the data for the system.
Step 2: Initialize parameter of algorithm and count t.
Step 3: Generate initial population by the usable uniform design.
Step 4: Evaluate the objective function and update count t.
Step 5: Identify the Fit best (t) of the current run t.
Step 6: Generate selection offspring using stochastic selection operation.
Step 7: Generate crossover offspring using scattered crossover operation.
Step 8: Generate mutation offspring using gaussian mutation operation.
Step 9: Take final point from the genetic algorithm as the initial point of the hybrid (PS) function.
Step 10: While (termination criterion not met).

The termination is done when a specified number of iterations met.

V. SIMULATION RESULTS

The proposed HGA approach was tested with two practical test cases of EDP with valve-point effects. The software was written in MATLAB 7.0.1 and executed on a Pentium-IV 2.99 GHz personal computer. Hereinafter, the results represent runs of the proposed method for the test case.

V-1 Case 1

This test case comprises of thirteen generating units, the complexity and non-linearity to the solution procedure is increased. The expected power demands to be met by all thirteen generating units is 2520 MW [19]. The system data can be found from [1, 2]. The problem has a number of local optimum points as there are more possibilities for any method to stick on any one of the local optimum points. The final fuel best results costs obtained using the GA-SA, EP-SQP, PSO-SQP and the proposed HGA method for power demand of 2520 MW with minimum cost of US$ 24163 h-1 is given in Table 1. The table reports the dispatch results of the various methods [20], EP-SQP, PSO-GA-SQP and the proposed method for a load demand of 2520 MW.

<table>
<thead>
<tr>
<th>Generator</th>
<th>Unit generation (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>628.23</td>
</tr>
<tr>
<td>2</td>
<td>299.22</td>
</tr>
<tr>
<td>3</td>
<td>299.17</td>
</tr>
</tbody>
</table>

It is clear from Table 1; the cost value obtained by the proposed method is comparatively less compared to the other methods.

Fig. 1 shows the PS phase convergence characteristics of the HGA method for power demand of 2520 MW.

V-2 Case 2

This test case comprises of 40 generating units. This is a larger system. The number of local optima, complexity and non-linearity to the solution procedure is enormously increased. The required power demand to be met by all the forty generating units is 10,500 MW. The system data can be found from [1,2].

<table>
<thead>
<tr>
<th>Method</th>
<th>Best cost (US$h^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EP[1, 2]</td>
<td>122624.35</td>
</tr>
<tr>
<td>MPSO[21]</td>
<td>122252.27</td>
</tr>
<tr>
<td>PSO[15]</td>
<td>123930.45</td>
</tr>
<tr>
<td>PSO-SQP[15]</td>
<td>122094.67</td>
</tr>
<tr>
<td>DEC(2)-SQP(1)[22]</td>
<td>121741.98</td>
</tr>
<tr>
<td>HGA</td>
<td>121424.48</td>
</tr>
</tbody>
</table>

Table 2 Comparison of fuel costs for case 2
The final fuel costs obtained using the EP, EP-SQP, PSO, PSO- SQP, MPSO, DEC(2)-SQP(1) and the proposed method were summarized in Table 2. It is clear from Table 2, HGA has the best probability of the cost value amongst all the methods in this test case.

The best results obtained for solution vector, with HGA with minimum cost of US$ 121158 h⁻¹ is given in Table 3.

<table>
<thead>
<tr>
<th>Power</th>
<th>Generation</th>
<th>Power</th>
<th>Generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>114.0000</td>
<td>21</td>
<td>523.6402</td>
</tr>
<tr>
<td>2</td>
<td>113.9998</td>
<td>22</td>
<td>523.6412</td>
</tr>
<tr>
<td>3</td>
<td>97.7662</td>
<td>23</td>
<td>523.6412</td>
</tr>
<tr>
<td>4</td>
<td>183.0928</td>
<td>24</td>
<td>523.6445</td>
</tr>
<tr>
<td>5</td>
<td>92.2552</td>
<td>25</td>
<td>523.6436</td>
</tr>
<tr>
<td>6</td>
<td>140.0000</td>
<td>26</td>
<td>523.6497</td>
</tr>
<tr>
<td>7</td>
<td>283.9629</td>
<td>27</td>
<td>10.3613</td>
</tr>
<tr>
<td>8</td>
<td>284.9659</td>
<td>28</td>
<td>10.3613</td>
</tr>
<tr>
<td>9</td>
<td>284.9659</td>
<td>29</td>
<td>10.3613</td>
</tr>
<tr>
<td>10</td>
<td>194.3611</td>
<td>30</td>
<td>97.0000</td>
</tr>
<tr>
<td>11</td>
<td>94.3613</td>
<td>31</td>
<td>190.0000</td>
</tr>
<tr>
<td>12</td>
<td>169.1615</td>
<td>32</td>
<td>190.0000</td>
</tr>
<tr>
<td>13</td>
<td>153.6114</td>
<td>33</td>
<td>190.0000</td>
</tr>
<tr>
<td>14</td>
<td>294.8852</td>
<td>34</td>
<td>165.1726</td>
</tr>
<tr>
<td>15</td>
<td>384.6405</td>
<td>35</td>
<td>200.0000</td>
</tr>
<tr>
<td>16</td>
<td>384.6403</td>
<td>36</td>
<td>199.9993</td>
</tr>
<tr>
<td>17</td>
<td>479.6433</td>
<td>37</td>
<td>110.0000</td>
</tr>
<tr>
<td>18</td>
<td>479.6412</td>
<td>38</td>
<td>110.0000</td>
</tr>
<tr>
<td>19</td>
<td>511.6417</td>
<td>39</td>
<td>109.9996</td>
</tr>
<tr>
<td>20</td>
<td>511.6416</td>
<td>40</td>
<td>511.6416</td>
</tr>
</tbody>
</table>

Fig. 2 shows the PS phase convergence characteristics of HGA. Hence, for power system ELD problems of greater size with more non-linearities, the proposed method is proved to be the best algorithm amongst all the methods.

VI. DISCUSSION AND CONCLUSION

Traditionally, to solve the EDP effectively, conventional techniques require convex cost function and strict continuity of the search space. But practically the incremental fuel-cost curves of the generating units are inherently highly non-linear and non-continuous. GA is an important tool for solving complex optimization problems, being applied to solve various problems in various diverse fields. It was also effectively used in solving complex problems in the power system field such as EDP.

GA is faster in finding the high performance region but displays difficulties in performing local search for complex functions. It leads to premature convergence and also has a poor fine tuning of the final solution. To overcome these drawbacks, GA was integrated with PS. This technique is used to solve the EDP with incremental fuel-cost functions taking valve-point effects into account. PS proves itself as a best non-linear programming method to solve the constrained optimization problem. The PS can explore the search space quickly and guarantee a local optimum solution. But the method is sensitive to the initial point. The hybrid approach for solving the EDP of units with value-point effects produces quality solutions compared to the one produced by these techniques when applied separately.

The performance of the hybrid method was tested for two EDP test cases with valve-point effects included and compared with the results obtained using the methods reported in recent literature. The results show that the proposed HGA performed much better than other methods compared in terms of convergence performance, minimum cost and probability of attaining better solutions.

REFERENCES


