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GENETIC SEARCH FOR AN OPTIMAL POWER FLOW SOLUTION FROM A HIGH DENSITY CLUSTER

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ABSTRACT
This paper presents a novel method for the solution of optimal power flow problem. The algorithm of the proposed method can be unfolded into three stages. In the first, a suboptimal solution is obtained by a conventional analytical method. In the second, a high density cluster, which consists of other suboptimal data points in the vicinity of the first are formed with the help of density-based cluster algorithm. In the final stage, a genetic algorithm based search is carried out for the exact optimal solution from a low population sized, high density cluster. The final optimal solution thoroughly satisfies the well defined fitness function. A standard IEEE 30-bus test system is considered for the simulation study. Numerical results are presented and compared with the results of other approaches in a judicious way.

KEY WORDS
Optimal Power Flow, Lagrange Method, Density based Cluster Algorithm, High Density Cluster, Genetic Search and Fitness function.

1. Introduction

The growth of a country can be attributed to the demand for electrical energy. However, the demand depends on cost of energy. A saving in the cost of generation represents there is a significant reduction in fuel, maintenance and other operational costs. The problem of Optimal Power Flow (OPF) is generally stated as the optimal allocation of given load amongst the units in operation in such a manner that the minimum overall cost of generation is obtained. Basically OPF is an optimization problem. Regardless of objective function, the OPF should be solved so that the entire set of equality or inequality constraints, all the necessary and sufficient conditions of control parameters etc. must be thoroughly are satisfied. OPF problem was first discussed by Carpenter [1]. The area of OPF has warranted a great deal of attention from operating and planning engineers. In the recent and past, researchers have contributed significantly in the area of OPF and many methods have been proposed. These methods basically can be grouped into analytical and *intelligent methods*.

Majority of analytical or mathematical programming methods includes [2] Lambda Iteration, Gradient Search, Newton's, Linear programming and Interior point methods.

OPF solution using any of the modified analytical methods can be referred in [3-13]. It may be observed these methods have following general limitations:

- They are not guaranteed to converge to global optimum of the general non convex problems like OPF.
- The methods may satisfy necessary conditions but not all the sufficient conditions.
- Inconsistency in the final results due to approximations made while linearising some of the nonlinear objective functions and constraints.
- Consideration of certain equality or inequality constraints makes difficulty in obtaining the solution.
- The process may converge slowly due to the requirement for the satisfaction of large number of constraints.

To overcome the difficulties in analytical methods, intelligent methods based on Artificial Neural Networks [14-15] or Genetic Algorithm (GA) methods have been proposed in the recent times. Solution for OPF by GA method has gained popularity [16-18] because of its robustness. In general GA is a typical heuristic method. The method is based in one hand on heuristic gradient ascension method (selection and crossover) and in another hand on a semi random exploration method (mutations). The GA method in solving optimization problems is well discussed in [19]. The general purpose GA has the following stages:

1) Formation of Chromosome and Selection of Population: GA operates on the encoded string of the problem parameters rather than the actual parameters of the system. Each string can be thought of as a chromosome that completely describes one candidate solution to the problem. Once the encoded structure of chromosome is formed, a population is then generated randomly which consists of certain number of chromosomes.

2) Parent Selection: In this process two chromosomes are selected from the population based on the Fitness Function (FF) value. Solutions with high FF have a high probability of contributing new offspring to the next generation.

3) Crossover process: In this, the chromosomes of the two parents are combined to form new chromosomes that inherit segments of information stored in parent chromosomes. Crossover operators described in the process are extremely important, since they are solely responsible for structure recombination and the convergence speed of GA. Even though the crossover operator exploiting information is included in the current generation, it does not produce new information.

4) Mutation Process: This operator is responsible for the injection of new information.

The FF evaluation and genetic evolution take part as the next part of GA, until when a maximum number of generations are reached. The following limitations may be observed in GA approach:

- The solution deteriorates with the increase of chromosome length. Hence to limit its size, limitations are imposed in consideration of number of control variables.
- GA method tends to fail with the more difficult problems and needs good problem knowledge to be tuned.
- Careless representation in any of the schemes that are used in the formation of chromosomes shall nullify the effectiveness of mutation and crossover operators.
- The use is restricted for small problems such as those handling less variables, constraints etc.
- GA is a stochastic approach where the problem is not guaranteed to be the optimum.

To overcome difficulties in conventional GA approaches, Anastasios G. Bakirtzis et.all [20] have proposed Enhanced Genetic Algorithm (EGA) for the solution of OPF problem. The EGA method has following features:

- The method considers control variables and constraints used in the OPF and penalty method treatment of the functional operating constraints. Control device parameters are treated as discrete control variables.
- Variable binary string length is used for better resolution to each control variable.
- The method avoids the unnecessary increase in the size of GA chromosome.
- *Problem-specific operators* incorporated in the EGA method makes the method suitable for solving larger OPF problems.

The test results presented in [20] are quite attractive. However the authors in their conclusions have presented some limitations of EGA method:

- The method is claimed as stochastic and also said the solution to OPF is not guaranteed to be optimum.
- Execution time is high.
- The quality of solution is found to be deteriorating with the increase in length of chromosome i.e the OPF problem size.
- If the size of power system is growing, the GA approach can produce more infeasible strings which may lead to wastage of computational time, memory etc.

Inspired by the results of EGA method and to overcome the general difficulties in GA or EGA approaches, a novel method is proposed in this paper. The method uses high density cluster DBSCAN and GA algorithms.

The purpose of Cluster Algorithms (CA) [21] can be stated as to divide a given group of objects in to a number groups or clusters in order that the objects in a particular cluster would be similar among the objects of the other ones. In the first stage of CA, an attempt is made to place N number of objects in M number of clusters according to some optimization criterion additive to clusters. Once the optimization criterion is selected, CA searches the space of all classifications and finds the one that satisfies the optimization function. For detailed cluster analysis that includes basic concepts, algorithms and types, the interested reader can refer in [22],. The DBSCAN is a density based clustering algorithm [22,23] that produces a partial clustering, in which the number of clusters is automatically determined by the algorithm. The points in low-density regions are classified as noise with high density difference and omitted and the points in high density cluster are similar points with low density difference.

A new technique for the solution of OPF based on GA search from a High Density Cluster named as in short form GAHDC is proposed in this paper. The objective of GAHDC is to retain advantages in Mathematical Programming techniques and to encounter the difficulties in GA Method. The GAHDC has mainly three stages. In the first stage a suboptimal solution for OPF problem is obtained by the conventional analytical method that considers lagrange multipliers, equality and inequality constraints of control variables, transmission loss B-Coefficients and penalty factors. The solution for OPF problem is treated as an approximate, owing to the listed limitations in the analytical methods. However this solution shall give a better insight in to the exact solution as the OPF is solved with the regular mathematical programming approach. In the second stage, a high density cluster by DBSCAN algorithm is formed surrounding the suboptimal solution that is obtained in the first stage. The high density cluster consists of several suboptimal solutions, one of which can be the exact one. In the third stage, GA search is carried out conventionally, for finding the exact solution. The solution in the last stage is the exact one, as is confirmed by the best FF value. This technique in contrast to GA method avoids the blind search, encountering with infeasible strings, and wastage of computational effort.

The remaining paper is organized as follows. Section-2 presents the OPF problem formulation. Section-3 provides the analytical method for the solution of OPF. Overview of clusters and general purpose DBSCAN algorithm can be seen in Section 4. The Algorithm for the proposed GAHDC method is presented in Section 5. Discussion and test results can be had in the Section 6 and finally conclusions are drawn in Section 7.

2. Optimal Power Flow Problem Formulation

The OPF problem can be formulated as an optimization problem [20] and is as follows:

$$\text{Min } C_T(x,u) \tag{1}$$

Subject to:

$$g(x,u) = 0 \tag{2}$$

$$h(x,u) \le 0 \tag{3}$$

$$u \in U \tag{4}$$

Where

$$x = [\theta^T, U_L^T] \tag{5}$$

$$u = [P_G^T \; U_G^T \quad t^T \; b_{sh}^T]^T \tag{6}$$

where θ: Bus voltage angle vector; U_L = Load Bus (PQ) voltage magnitude vector; P_G = Unit Active power output vector; U_G = Generation (PV) bus voltage magnitude vector; t = Transformer tap settings; b_{sh} = bus shunt admittance vector; x = System state vector; u = system control vector;

The equality constraints (2) are the nonlinear power flow equations. The inequality constraints (3) are functional operating constraints, such as: branch flow limits (MVA, MW or A), Load bus voltage magnitudes limits, generator reactive power limits and Slack bus active power output limits

The constraints in (4) define the feasibility region of problem control variables such as: Unit active power limits, generator bus voltage magnitude limits, transformer tap setting limits (discrete values) and bus shunt admittance limits (continuous or discrete control)

3. Analytical Method for the Solution of OPF

Mathematically, the problem is defined as:

$$C_T = \sum_{i=1}^{n} (\gamma_i P_i^2 + \beta_i P_i + \alpha_i) \; \$/hr \tag{7}$$

Subject to the energy balance equation

$\sum_{i=1}^{n} p_i = p_D + p_L$ and the inequality constrains

$$p_{i_{\min}} \le p_i \le p_{i_{\max}} \quad (i = 1,2,3,......n) \tag{8}$$

where γ_i, β_i, α_i are the cost coefficients, P_D= load demand; P_i = real power generation i^{th} Machine; n = number of generation buses and P_L = transmission power loss.

$$\frac{dC_1}{dP_1}\frac{1}{1-\frac{\partial P_L}{\partial P_1}} = \frac{dC_2}{dP_2}\frac{1}{1-\frac{\partial P_L}{\partial P_2}} = ... = \frac{dC_{NG}}{dP_{NG}}\frac{1}{1-\frac{\partial P_L}{\partial P_{NG}}} = \lambda \tag{9}$$

The co-ordination equation of i^{th} Machine is:

$$L_i \frac{dC_i}{dP_i} = \lambda \tag{10}$$

The penalty factor of i^{th} Machine is: $L_i = \dfrac{1}{1-\dfrac{\partial P_L}{\partial P_i}}$

$$(i=1,2,3,4. \ldots .n) \tag{11}$$

where $\dfrac{\partial P_L}{\partial P_i} =$ is the incremental transmission loss of i^{th} Machine and λ = incremental cost of received power units \$/M Whr.

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j$$

For n generator system B-matrix is n x n symmetric matrix,

$$B = \begin{bmatrix} B_{11} & B_{12} & K & B_{1n} \\ B_{21} & B_{22} & K & B_{2n} \\ M & M & & M \\ B_{n1} & B_{n2} & L & B_{nn} \end{bmatrix} \tag{12}$$

The algorithm for solving (7-9) by the iterative process can be referred in [2].

4. Cluster Analysis and DBSCAN Algorithm

Cluster Analysis divides data into groups or *Clusters* that are meaningful and useful. The analysis is sometimes useful as it provides a starting point for other purposes, such as data summarization. The clusters are classified into [22]: Well-Separated, Proto-type, Graph-based, Conceptual type and Density based. A *Density based* is a cluster with dense region of objects that is surrounded by a region of data points of similar kind or of with low density difference. In the Fig.1, a high density cluster A is shown separated from the low density clusters B and C. In the context of high density clusters, the following definitions are important: 1) *Core Points*: These points are in the interior of a density based cluster. A point is a core point if the number of points with in a given neighborhood around the point are as determined by the distance parameter Eps. 2) *Border Points*: A border point is not a core point, but falls within the neighborhood of a core point. In Fig.1 Cluster B is formed with these points. 3) *Noise Points*: A noise point is any point that is neither a core nor a border point.

In Fig.1, the Cluster C is formed with these points.

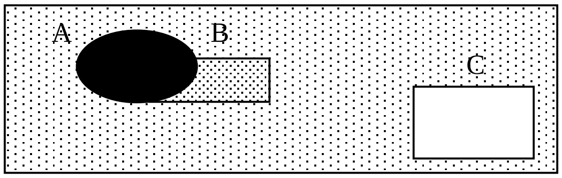

Figure 1. Density-based clusters: Clusters are regions of high density separated from by the regions of low density

4.1 DBSCAN Algorithm

This algorithm can be described as follows: Any two core points that are close enough-within a distance of E_{ps} of one another are put in the same cluster. Any border point that is close enough to core point is put in the same core cluster, During the process, the remaining border points and all noise points are eliminated. The general purpose DBSCAN Algorithm is presented below [22]:

1. Label all points as core, border and noise points.
2. Eliminate noise points.
3. Put an edge between all core points that are within E_{ps} of each other.
4. Make each group of connected core points into a separate cluster.
5. Assign each border point to one of the clusters of its associated core points.

The proposed method for the solution of OPF problem is presented in the next section.

5. Genetic Search for the OPF Solution from a High Density (GAHDC Method)

The GAHDC can be unfolded into three main stages as shown in the Flowchart (Fig.2).

Stage-1: In this stage, OPF problem is treated conventionally by the analytical method presented in the section 3. All the parameters described in the equations (2-4) are considered and iterative process is carried for the OPF solution by Lagrange's method [2] of solving the optimization problems. Owing to the limitations of the analytical methods, this solution is taken only as a *suboptimal* one. However due to consideration of constraints of control parameters this solution gives a better insight in to the high density cluster.

Stage-2: In this stage, the DBSCAN algorithm is implemented to form the high density cluster. The suboptimal solution obtained in the first stage is first encoded into a chromosome. This chromosome is treated as one of the core point and the FF value of this chromosome is calculated and used as E_{ps}. Then the crossover process is carried for generating new population consisting of other chromosomes (or say other suboptimal solutions) subject to FF values of these chromosomes within E_{ps}. This forms a high density cluster and thoroughly avoids noise points and border points which are regarded as infeasible solutions. It should be informed here that, the length of chromosome in the proposed method is reduced due to non consideration of certain control parameters. This reduces the size of population of the high density cluster to a greater extent. However, the constraints of the control parameters are considered in the third stage before arriving to the exact optimal solution

Stage-3: Finally the exact solution for OPF is obtained from the high density cluster, subject to the satisfaction of best FF value, constraints and convergence of Load Flow problem.

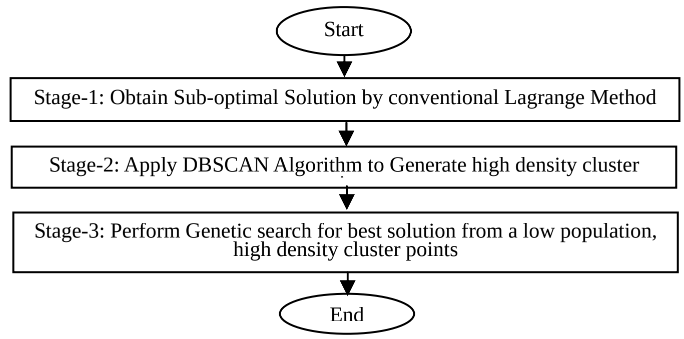

Figure 2. Flow Chart: Stages in the Proposed GAHDC Methodology

The GAHDC has the following major advantages over the EGA method [20]:

- Length of Chromosome is reduced and hence the size of population is reduced.
- Numbers of generations are reduced. This makes the computational effort simple and effective.
- The problem of use of specific mutation or crossover operators is avoided, makes the OPF as another simple GA search problem.
- Blind search is avoided.
- The process begins with no insignificant chromosomes.
- System nonlinearities are somewhat considered as the initial chromosome is obtained from the mathematical programming of nonlinear equations.

The Algorithm of proposed method is presented below:

5.1 GAHDC Algorithm

The implementation of GAHDC involves the following steps:

Step-1; *Obtain Initial Solution for OPF Problem.* By considering equality and inequality constrains, limits for control parameters etc. represented in (2) to (6), solve OPF problem (1) by analytical Lagrange's Method [2]. The scheduled generation obtained is treated as the suboptimal solution.

Step-2: *Formation of Siring for Core Point in High-Density Cluster* The suboptimal solution is then encoded into a string to form a chromosome in High Density Cluster. The structure of the chromosome used in EGA[2] and GAHDC are shown in the Figs.3 and 4. The interested reader can refer [20] for complete information for string formation. The difference in string lengths of chromosomes can be observed in both the methods.

P_{G1}	:	P_{Gn}	U_{G1}	:	U_{Gn}	t_1	:	t_n	b_{sh1}	:	b_{shn}
Unit active Power Outputs			Generator bus voltage magnitudes			Transformer tap settings			Bus shunt admittances		

Figure 3. String Structure in EGA Method [20]

P_{G1}	. . . . . .	P_{Gn}
Unit active Power Outputs		

Figure 4. String Structure in GAHDC Method

Step-3: *Find measure of distance for core points E_{ps} from the initial suboptimal solution* To find E_{ps} value, the FF of initial chromosome is calculated after decoding the chromosome and by evaluating its FF.

Decoding of strings: The following equation [20] is used to decode the chromosome into actual continuous control variables.

$$u_i = u_i^{\min} + (u_i^{\max} - u_i^{\min}).\frac{k}{2^{Nni-1}} \tag{13}$$

Then the following formula is implemented to determine FF value:

$$FF = \frac{A}{\sum_{i=1}^{N_G} C_T(P_{Gi}) + \sum_{j=1}^{N_c} Wj.Pen_j} = E_{Ps} \tag{14}$$

$$Pen_i = |hj(x,u)|.H(hj(x,u))$$

where k is decimal number to which the binary number in a gene is decoded and N_{ui} is the gene length used for encoding control variable u_i.C_T is the fuel cost of individual generations. $h_j(x, u)$ = violation of the j^{th} functional operating constraint if positive; $H(.)$ = Heaviside (step) function; N_G= Number of units; N_C = Number of functional operating constraints; A = Constant: W_j = Weighting factor of functional operating constraints j.

Step-4:Generate population for High Density Cluster Other High density cluster points are formed by the following method. By adding or by subtracting a small incremental value to the suboptimal solution, the population is then generated. The chromosomes in this population are the core points, as their FF values are compared and found within the region of E_{ps}.

Step-5: *GA Search for the exact OPF solution* Arrange core points in descending order with respect to their FF values. Select a core chromosome with highest FF value. Evaluate (1) subject to (2) to (6). If any violation of constraints, the next core chromosome in the list is selected. The Process is repeated until the desired chromosome which satisfies all constraints is selected.

Table 1: Test results of GAHDC and EGA method

GEN NO	BUS NO	BUS VOLTAGES		ACTIVE POWER GENERATION		COST OF GENERATION	
		EGA	GAHDC	EGA	GAHDC	EGA	GAHDC
1	1	1.050	1.0600	176.20	176.0439	468.84	468.3056
2	2	1.038	1.0430	48.75	48.8660	126.89	127.3034
3	5	1.012	1.0100	21.44	21.2030	50.19	49.3009
4	8	1.020	1.0100	21.95	22.4772	75.35	77.2442
5	11	1.087	1.082	12.42	12.2821	41.13	40.6177
6	13	1.067	1.0710	12.02	12.00	39.67	39.600
TOTAL				**292.79**	**292.8722**	**802.06**	**802.3719**

Table 2: Generation Schedule difference of GAHDC Compared to EGA

	Total Active Power Generation		**Transmission Losses**		**Total cost**		**CPU Time**
Parameter	in MW	% High	In MW	% High	In $/hr	% High	in Sec
GAHDC	292.8722	0.028	9.47	0.84	802.3719	0.038	**15**
EGA	292.79	----	9.39	----	802.06	----	**85**

6. Simulation Results and Discussion

The GAHDC performance is evaluated on the standard IEEE 30-bus test system. The test is carried with a 1.4-GHz Pentium-IV PC. The study is carried for a total system load of 283.4 MW. The performance of GAHDC is compared with the results of EGA method and is tabulated in Table-1. For a given system load, the total generation in the system by GAHDC method is found slightly higher compared to that of EGA method. The % high values are presented in Table-2. The results in the Table, when compared to their numerical difference can be regarded as much similar. The EGA for an IEEE30-Bus system is carried with a computer having the same configuration as mentioned above. This indicates the computational work in terms of CPU time can be compared. The GAHDC method has completed simulation test in 15 seconds in contrast to 85 seconds that is taken by EGA method. The authors of EGA method in their conclusions have mentioned the high execution time of their method This proves the GAHDC method is quite acceptable for large size power systems and for on-line studies.

7. Conclusion

A novel method for the solution of Optimal Power Flow is proposed in this paper. The limitations of analytical and intelligent methods are presented. The method was developed on the basis of analytical method, High Density DBSCAN algorithm and GA. It has been found the method has advantages like population size reduction, minimal cross over operation, reduction in the length of chromosome and consideration of nonlinearities of the system. The performance of the method is tested on standard IEEE 30 bys system. Numerical results are presented and compared with that of popular Genetic approaches. Though there is no much difference in numerical values, but the proposed method has advantages of minimal computational effort and a high reduction in CPU time. This suggests the method can be suitable for online applications such as the present Optimal Power Flow problem.

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