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A Novel Approach of Economic Load Dispatch Problems Using Atmosphere Clouds Model Optimization Algorithm

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Abstract: The growing costs of fuel and operation of power generating units warrant improvement of optimization methodologies for Economic Load Dispatch (ELD) problems. The practical ELD problems have non-convex objective functions with equality and inequality constraints that make it much harder to find the global optimum using any mathematical algorithms. Modern optimization algorithms are often meta-heuristic and they are very promising in solving nonlinear programming problems. This paper presents a novel approach to determining the feasible optimal solution of the ELD problems using the recently developed Atmosphere Clouds Model Optimization Algorithm (ACMOA). Many nonlinear characteristics of power generators and their operational constraints, such as generation limitations, prohibited operating zones, ramp rate limits, transmission loss and nonlinear cost functions, were all contemplated for practical operation. To demonstrate the efficiency and applicability of the proposed method, we study four ELD test system (IEEE 30 Bus Test Case) having non-convex solution spaces and compared with some of the most recently published ELD solution methods.

Key words: Economic Load Dispatch · ACMOA · Optimization Algorithms

INTRODUCTION

Since an engineer is always concerned with the cost of products and services, the efficient optimum economic operation and planning of electric power generation system have always occupied an important position in the electric power industry. A saving in the operation of the system of a small percent represents a significant reduction in operating cost as well as in the quantities of fuel consumed. The classic problem is the economic load dispatch of generating systems to achieve minimum operating cost. Traditional algorithms like lambda iteration, base point participation factor, gradient method and Newton method can solve this ELD problems effectively if and only if the fuel-cost curves of the generating units are piece-wise linear and monotonically increasing. Practically the input to output characteristics of the generating units are highly non-linear, non-smooth and discrete in nature owing to prohibited operating zones, ramp rate limits and multi-fuel effects. Thus the resultant ELD becomes a challenging non-convex optimization problem, which isdifficult to solve using the traditional methods.

Literature Survey: Economic dispatch (ED) is an optimization problem where optimal generation for each generator is determined to minimize total fuel costs, subject to equality constraints on power balance and inequality constraints on power outputs. Moreover, transfer losses, generation rate changes and line flows may also be considered.

A variety of techniques may be used to solve ED problems; some are based on classical optimization methods, such as linear or quadratic programming [1-2], while others use artificial intelligence or heuristic algorithms. Classical techniques are highly sensitive to a selection of the starting point and often converge to a local optimum or even diverge altogether. Linear

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programming methods are generally fast and reliable but use piecewise linear cost approximation which reduces accuracy. Non-linear programming methods, on the other hand, have convergence problems and often result in very complex algorithms. Newton based algorithms suffer from difficulties associated with handling a large number of inequality constraints [3].

More recently, heuristic search techniques – such as particle swarm optimization (PSO) [4-6] and genetic algorithm (GA) [7] – have also been considered in the context of ED. In addition, differential evolution algorithms were implemented to solve the ED problem [8-10]. Differential evolution (DE) is a stochastic search based method, which can present a simple structure, convergence speed, versatility and robustness. However, DE fast convergence might lead the direction of the search toward a local optimal and premature solution. Finally, the use of harmony search (HS) method to find the global or near global solution for the ED problem can be found in [11, 12]. HS is considered as a stochastic random search method, which does not need any information about the derivative. Nevertheless, HS has some insufficiencies associated with the premature convergence in its performance. A combined Particle Swarm Optimization and Sequential Quadratic Programming (PSO–SQP) algorithm was developed in [13], where PSO is the main optimizer and the SQP is used to ?ne tune the PSO solution. However, since SQP is a gradient dependent method, its application to non-continuous, non-differentiable and multimodal problems, such as ED, might not lead to an optimal solution.

An increasing international concern about environment also affects the field of power generation where environmental issues are addressed directly. In another hybrid approach [14], the Differential Evolution (DE) and the Sequential Quadratic Programming (SQP) were combined into a single algorithm and used on 13 and 40 thermal units whose incremental fuel cost functions contain the valve point loading effect. In [15] the authors combined three evolutionary methods to solve a fuzzy modelled Unit Commitment Problem (UCP). The three methods are Tabu Search (TS), Particle Swarm Optimization (PSO) and Sequential Quadratic Programming (SQP) (referred to as a hybrid TS-PSO-SQP). TS is used to solve the combinatorial sub-problem of the UCP.

In [16], the modified sub gradient (MSG) and the harmony search Sequential (HS) algorithms were combined into a single algorithm and used on 3, 5 and 6 thermal units whose incremental fuel cost functions contain the valve point loading effect. In [17] the authors to solve Unit Commitment Problem through modified group search optimizer (MGSO) method. Samir Sayah and Abdellatif Hamouda [18] discusses the non convex economic dispatch problems through a hybrid DE based on PSO.

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.The main objective of this study is to introduce a new Atmospheric Cloud Model Optimization (ACMO) [19] in the context of power system economic dispatch problem with a valve-point effect. The results are obtained from an IEEE 30 bus 5 machine system solved with different methods in the literature. The resulting optimal solution values are compared with the solution values in the literature and the results are discussed.

Atmosphere Clouds Model Optimization: Inspired from the cloud's behavior in the nature world, in this work we have proposed a novel numerical stochastic optimization algorithm by simulating the generation behavior, move behavior and spread behavior of cloud in a simple way, which is designated as Atmosphere Clouds Model Optimization (ACMO) algorithm. In this algorithm, a novel optimization method reverse search method is presented, in which the whole population spread from the current optimal positions to the whole search space in a `cloud' existence pattern, instead of clustering from all directions to the optimal positions. This special optimization method can make the ACMO algorithm maintain high population diversity and prevent the algorithm from trapping into local optima.

ACMO Algorithm: The ACMO algorithm is abstracted from the generation behavior, move behavior and spread behavior of cloud in the search space.

The abstract process of ACMO algorithm is as follows:

- Firstly the whole search space is divided into many disjoint regions according to some rules and each region has its own humidity value and air pressure value;

- The behavior of clouds must follow rules listed below:
- Clouds can only be generated in regions whose humidity values are higher than one certain threshold;
- Under the action of wind, clouds move from regions with higher air pressure value to regions with lower air pressure value;
- In the moving process, the droplets of one cloud would spread or gather according to the air pressure difference between the region where this cloud locates before move behavior and region where cloud locates after move behavior;
- One cloud is regarded as disappeared when its coverage exceeds a certain value or its droplets number is less than a certain value;
- The humidity value and air pressure value of all regions are updated every time after the generation behavior, move behavior and spread behavior of clouds.

Here are the definitions of some important concepts in ACMO algorithm.

Definition 1: Suppose U is the universe, the region is defined as subspace after the division of U according to some rules. In this paper we suppose each dimension of U is divided into M small interval.

$$I_i = \frac{u_i - u_i}{M}, i = 1,2,...D \tag{1}$$

where I_i is the length of interval in i^{th} dimension, u_i and l_i express the upper.

Boundary and lower boundary of i dimension respectively, D is the dimension. Then the whole search space would be divided into MD regions and each of them meets the following properties:

$$\begin{cases} \bigcup_{i=1}^{M^D} U_i = U \\ U_i \cap U_j = \varnothing, \forall_i, j \in \{1,2,...M^D\}, i \neq j \end{cases} \tag{2}$$

Definition 2: Cloud C is defined as a qualitative concept in U and x is the.

Stochastic implementation of C, x U Each x is called one cloud droplet and the distribution of x in U is called cloud. In this paper the concept of cloud is described by the normal cloud model. So the qualitative characteristic of one cloud can be described by the three digital characteristics (Ex, En, He) and the droplets number n, where Ex (Expected value), En (Entropy) and He (Hyper entropy) of one cloud express the center position of cloud, the cover range of cloud and the thickness of cloud respectively. Suppose there are m clouds in iteration t, the expression of which is:

$$C^t = \{C_1^t, C_2^t, ...C_j^t, ..., C_m^t\} \tag{3}$$

The droplets numbers of clouds can be expressed as:

$$n^t = \{n_1^t, n_2^t, ...n_j^t, ..., n_m^t\} \tag{4}$$

The droplets numbers of all clouds must meet the two properties listed below:

$$\begin{cases} n_j > dN, \forall j \neq 1,2,...m \\ \sum_{j=1}^{n} n_j \leq N \end{cases} \tag{5}$$

where N expresses the smallest value of the droplets number in one cloud, N expresses maximum value of droplets number in every iteration. For the expressive convenience the three digital characteristics (Ex, En, He) of one cloud is marked as C. Ex, C. En, C. He. The droplets distribution of one cloud can be expressed as:

C(x) ~ N(C. Ex, Ex'2 (6)

where En' N(C . En, (C. He)2), N(C. En, (C. He)2) expresses standard normal random variable when C. En indicates the expectation, (C. He)2 is the variance. Each region has its humidity value and air pressure value. The definitions of them are given as follows.

Definition 3: The humidity value of one region is defined as the best fitness value found in this region so far, the expression of which is:

$$X_i^* = \arg\ \max f(x), H_i = f(X_i^*) \tag{7}$$

where f is the objective function; x express the droplets which dropped into region Ui once; X*i indicates the position with the maximum fitness value, which expresses the humidity value of region Ui.

Definition 4: The air pressure value of one region is defined as how many times this region has been searched, which is expressed as:

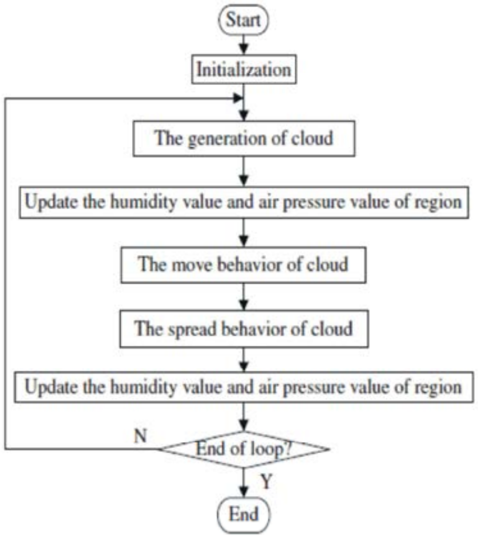

Fig. 1: Flowchart of the ACMO algorithm

$$P_i = CNT(x \in U_i), \quad i = 1,2,...M^D \tag{8}$$

where CNT function is used to do the statistics of data meeting requirement. The specific optimization process of ACMO algorithm is addressed in details as follows. The flowchart of ACMO algorithm is shown in Fig. 1.

Problem Description: The main objective of ELD is to minimize the total generation cost of the power system within a defined interval. The basic ELD considers the power balance constraint apart from the generating capacity limits. However, a practical ELD must take a variety of practical operating conditions into consideration to provide the completeness for the ELD problem formulation. These include transmission losses, valve-point effects, prohibited operating zones, ramp rate limits and spinning reserve etc.

Objective Constraints

Equality Constraints: Power balance is equality constraint. In other word, the total power generation must cover the total demand (PD) and total real power loss in transmission lines (Ploss). The condition of equality constrain can be expressed as:

$$\sum_{i=1}^{N} P_i - P_D - P_{loss} = 0 \tag{9}$$

where, PD is the total load of consumers and PLoss is the total transmission network losses. Loss of transmission network is expressed as a quadratic function of the generators' power outputs as shown in.

$$P_L = \sum_{i=1}^{ng}\sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{ng} B_{oi} P_i + B_{oo} \tag{10}$$

where, Bij is the ijth element of the loss coefficient square matrix. B0i and B00 are the ith element of the loss coefficient vector and the loss coefficient constant, respectively.

Generation Capacity Constraints: For unflinching operation, the generator outputs and bus voltage constraints by lower and upper limits as follows:

$$P_i^{\min} \leq P_i \leq P_i^{\max}, Q_i^{\min} \leq Q_i \leq Q_i^{\max}, V_i^{\min} \leq V_i \leq V_i^{\max} \tag{11}$$

where Pimin is the minimum loading limit below which it is uneconomical to operate the unit and Pimax is the maximum output limit. Eq. (4.20) shows minimum and maximum domain for reactive power and voltage magnitude of the ith transmission line, respectively.

Line Flow Constraints: One important constrain of EED problem is determinate of constrain of Line, because any line have a limit capability for current power, the limit can checking after load flow for power system. Therefore, this paper discussed the solution of EED problem with line flow constraints through the application of supposed algorithm. It's constrains can be modeled by:

$$|P_{Lf,k}| \leq P_{Lf,k}^{\max}, k = 1,2,...,L \tag{12}$$

where PLf, k is the real power flow of line k; $P^{\max}_{Lf}$, k is the power flow upper limit of line k and L is the number of transmission lines.

Prohibited Operating Zone Constraints: Faults in the generators themselves or in the associated auxiliaries such as boilers, feed pumps, etc., may cause instability in certain ranges of generator power output. Consequently, discontinuities are produced in cost curves corresponding to the prohibited operating zones. So, there is a quest to avoid operation in these zones in order to economize the production. The prohibited operating zones constitute the following constraint for ED.

$$P_j \in \begin{cases} P_{j\min} \leq P_j \leq P_j^{LB_z} \\ P_j^{UB_{z-1}} \leq P_j \leq P_j^{LB_z} \quad j = 1,2,...,N_g \\ P_j^{UB_z} \leq P_j \leq P_{j\max} \end{cases} \tag{13}$$

where P_j^{LBz} and P_j^{UBz} are lower and upper bounds of the z^{th} prohibited zone of unit j; z is the index of prohibited zones.

Environmental Objective: The atmospheric pollution caused by the fossil fired generator contains sulfur oxides (SOx), nitrogen oxides (NOx), carbon dioxide (CO2) and so on. For simplicity, the total emission of these pollutants is expressed as a sum of a quadratic and exponential function.

$$\min E = \sum_{i=1}^{N} [\alpha_i + \beta_i . P_i + \gamma_i . P_i^2 + \eta_i . \exp(\delta_i . P_i)] \tag{14}$$

Generator Operation and Ramp Limit Constraints:

$$P_i^{min} \le P_i \le P_i^{max}, \max(P_i^{min}, P_i^0 - DR_i) \le \min(P_i^{max}, P_i^0 + UR_i) P_i \in A_{ai} \tag{15}$$

where Pi min and Pi max are lower and upper bounds for power outputs of the ith generating unit

System Spinning Reserve Constraints: Spinning reserve is the amount of synchronized generation that can be used to pickup source contingencies or load increase. The available system reserve should be at least equal to the system requirement to overcome contingencies. The system spinning reserve constraint can be formulated as follows:

$$\sum_i S_i \ge S_R \tag{15}$$

With

$$S_i = \min\{(P_i^{max} - P_i), S_i^{max}\}, \forall_i \in (\Omega - \Psi)$$

$$S_i = 0, \forall_i \in \Psi$$

where Si is the spinning reserve of unit i; SR is the system spinning reserve requirement; Simax is the maximum spinning reserve contribution of unit i; is the set of all online units and is the set of units with prohibited zones. Note that for unit with prohibited operating zones, these zones strictly limit the unit to regulate system load because load regulation may result in its falling into a certain prohibited operating zones. As a result, a unit which has prohibited operating zones does not contribute spinning reserve to the system.

RESULTS AND DISCUSSION

The efficiency of the ACMO based method is tested on IEEE-30 bus system. The algorithm is coded in MATLAB 7.8 environment. A Core2 Duo processor based PC is used for the simulations. The base load condition is taken for the simulation and the system bus and line data are obtained from standard test case archive. The algorithm is run for 50 iterations with population of 100, number of droplets in one cloud of 50 and the threshold factor is 0.7. To demonstrate the effectiveness of the proposed algorithm, was tested and compared with Evolutionary Programming [20], Tabu Search [21], Hybrid Tabu Search/Simulated Annealing [22], Improved Tabu Search [23], Improved EP [24] and Self Adaptive Differential Evolution with Augmented Lagrange Multiplier Method [25] based on fuel cost characteristics like the valve point effect.

Table 1: Comparison of the optimum generator schedule, voltage and fuel costs with valve point effects

Optimal solution	EP	TS	TS/SA	ITS	IEP	SADE ALM	ACMO
PG1 (MW)	163.3230	155.7209	169.6563	172.9372	149.7331	193.2903	199.457
PG2 (MW)	54.5231	53.9911	53.6309	52.6262	52.0571	52.5735	51.7233
PG5 (MW)	24.1632	22.0452	20.8450	19.6310	23.2008	17.5458	13.8371
PG8 (MW)	29.6781	23.6846	19.8682	18.3666	33.4150	10.0000	7.1524
PG11 (MW)	18.2329	15.0305	17.2098	13.9383	16.5523	10.0000	11.3356
PG13 (MW)	15.9822	14.6462	13.4098	13.0921	16.0875	12.0000	10.4385
VG1 (p.u)	1.0500	1.0500	1.0500	1.0500	1.0500	1.0493	1.0377
VG2 (p.u)	1.0232	1.0209	1.0334	1.0298	1.0398	1.0271	1.0209
VG5 (p.u)	1.0187	1.0162	1.0140	1.0121	1.0145	1.0081	1.0347
VG8 (p.u)	1.0229	1.0276	1.0231	1.0107	1.0254	1.0109	1.0211
VG11 (p.u)	1.0908	1.0502	1.0602	1.0695	1.1000	1.0732	1.0393
VG13 (p.u)	1.0402	1.0218	1.0085	1.0214	1.0758	0.9634	1.0384
Fuel Costs ($/hr.)	955.508	956.498	959.563	969.109	953.573	944.031	922.5657

Table 2: Total generator fuel cost for the quadratic cost function

Algorithm	Fuel Cost ($/hr.)				Average computational time (minutes)
	Best Cost	Average Cost	Worst Cost	Standard Deviation of Cost	
EP	955.508	957.709	959.379	1.084	61.419
TS	956.498	958.456	960.261	1.070	88.210
TS/SA	959.563	962.889	966.023	2.146	65.109
ITS	969.109	977.170	985.533	6.191	85.138
IEP	953.573	956.460	958.263	1.720	93.583
SADE_ALM	944.031	954.800	964.794	5.731	16.160
ACMO	922.565	941.056	970.738	3.118	1.957

Cost Function with Valve Point Effect: In a steam turbine with multi stage inputs by a number of valves, the cost curve is not smooth. Fuel cost calculated using the quadratic cost curve will not be accurate as it considers the curve a smooth one. A sine function is added with the quadratic function to take into account the effect of valve points. In this case the cost function is taken with valve point effect. ACMO algorithm is run for fuel cost minimization as the objective. The real power settings shown in Table 1 are found to be the best one for cost minimization. The fuel cost obtained is 923.3765 USD/hr. It is lower than the cost reported in the recent literatures shown in references.

The line flows under non smooth cost functions are also shown in Table 2. The respective MVA flow of each line with its corresponding MVA rating is also given in this table. Figure 2 shows that the algorithm has converged to a better result and stays in the optimal fuel cost.

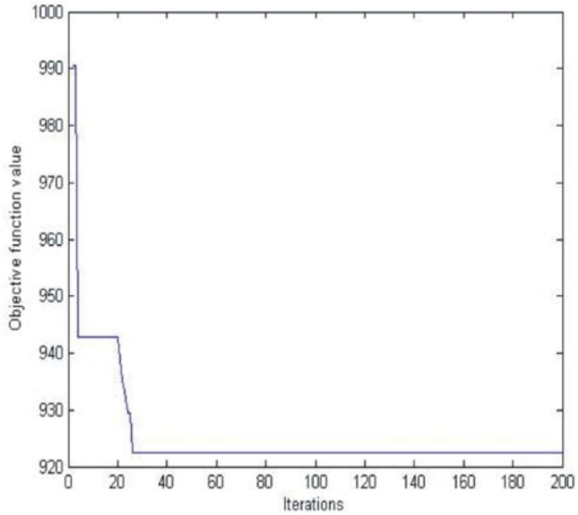

Fig. 2: Convergence of ACMO with valve point effect

Table 2 Line flows under non smooth fuel cost functions.

The total generator fuel cost for the quadratic cost function as shown in Table 3. The best, average and worst cost of proposed algorithm is compared with other evolution techniques given in this section The ACMO proved its performance in making the fuel cost is minimum as 923.3765 USD compared with other evolutionary techniques given in table. The average computational time for simulation is much less in minutes compared with other evolutionary techniques.

It is very clear from the results ACMO having superior performance compared with other evolutionary techniques for fuel cost function with optimal generator schedule.

CONCLUSION

In this work, a new nature inspired algorithm is implemented for the ELD problem. The numerical results clearly show that the proposed algorithm gives better results. The ACMO optimization algorithm outperforms the recently reported algorithms. The strength of the algorithm is proved with the non smooth objective functions,

The algorithm is with less number of operators and easy to be calculated in any computer language. Power system operation optimization problems can be attacked with this algorithm. Power system operators can use this algorithm for various optimization tasks.

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