

Cuckoo Search for Solving Economic Dispatch Load Problem

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Received June 20, 2013; revised July 20, 2013; accepted July 28, 2013

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ABSTRACT

Economic Load Dispatch (ELD) is a process of scheduling the required load demand among available generation units such that the fuel cost of operation is minimized. The ELD problem is formulated as a nonlinear constrained optimization problem with both equality and inequality constraints. In this paper, two test systems of the ELD problems are solved by adopting the Cuckoo Search (CS) Algorithm. A comparison of obtained simulation results by using the CS is carried out against six other swarm intelligence algorithms: Particle Swarm Optimization, Shuffled Frog Leaping Algorithm, Bacterial Foraging Optimization, Artificial Bee Colony, Harmony Search and Firefly Algorithm. The effectiveness of each swarm intelligence algorithm is demonstrated on a test system comprising three-generators and other containing six-generators. Results denote superiority of the Cuckoo Search Algorithm and confirm its potential to solve the ELD problem.

Keywords: Economic Dispatch Load; Cuckoo Search Algorithm; Swarm Intelligence; Optimization

1. Introduction

The electrical systems are interconnected in order to obtain the benefits of minimum generation costs, maximum reliability and best operational conditions, such as sharing of power reserve, improving the stability and operating on emergency situations [1]. Thus, the optimization problem of the economic dispatch of electrical power is relevant to accomplish requirements of quality and efficiency in power generation.

The economic load dispatch is an issue in which it has generated units available and connected to the power system. During the operational activity of the system, it must comply the expected load (system's demand), so that the sum of the power of the generating units is equal to the total load of the system and electrical losses.

The basic objective of the economic load dispatch problem of electrical power generation is the scaling of committed generating units outputs to find the consumer load demand at a minimal operating cost within a time interval (typically one hour), satisfying the inherent restrictions with the gathered generating units and the equality and inequality constraints imposed by the problem [2].

The economic dispatch for the operation of electrical

groups is described as a multi-objective mathematical programming problem, where the goal is to minimize the function that determines the fuel cost (objective function), stating an optimal generation profile, subject to satisfaction of the energy load power and the technical limits of the operating groups.

The economic dispatch problem has complex and nonlinear characteristics, and usually with the presence of equality and inequality constraints. Several methods have been used to solve this problem since it was introduced, for example, iterative method, gradient based techniques, interior points method, linear programming and dynamic programming. However, the conventional approaches used for the optimization of this problem are inadequate, because the solution can be retained in traps of local minima [1]. Furthermore, the classical dispatch algorithms require incremental cost curves to be monotonically increasing/piecewise linear and some approximation should be made to satisfy the requirements. However, the input/output characteristics of modern generating units are inherently highly non-linear. Therefore, more interests have been focused on the application of Computational Intelligence (AI) methods for solving this kind of problem.

Some heuristic methods explore not only features of the problems but particularly also the analogy with other optimization methods found in nature. Such heuristics are called metaheuristics and are independent of the problem being treated. Many metaheuristics were proposed based on population for solving unconstrained optimization problems. Since population-based optimization techniques are more effective than the gradient techniques in finding the global minimum, they have been preferred in many applications, because metaheuristic approaches allow the insertion of constraints in a smoother manner.

Several models of the economic load dispatch problem using population-based methods have also been addressed in some works of literature, including the use of methods such as Genetic Algorithms [2], Particle Swarm Optimization [3,4], Evolutionary Programming [5], Bacterial Foraging Optimization (BFO) [6], Ant Colony Optimization [7], Harmony Search [8], Biogeography-based Optimization [9] and Seeker Optimization Algorithm [10].

The fundamental principle of these algorithms, also referred to as bioinspired methods, uses a constructive method for obtaining the initial population (initial feasible solutions represented by individuals) and a local search technique to improve the solution within the population, whereas the individuals (solutions) of population are evolved according to specified rules that consider the exchange of information among individuals. This process drives the population towards obtaining an optimal solution. Such algorithms are also known as swarm intelligence algorithms [11].

This paper applies the recent Cuckoo Search (CS) algorithm [12] to solve the economic load dispatch problem. Our motivation for using this population-based algorithm is due to two primary reasons highlighted by its authors for a superior performance of this algorithm in contrast with others metaheuristics, as discussed in [12]: a fine balance of randomization and intensification, and less number of control parameters. First, for any metaheuristic algorithm, a good balance of intensive local search strategy and an efficient exploration of the whole search space will usually lead to a more efficient algorithm. So, the success or failure of a population-based algorithms depends on its ability to establish proper tradeoff between exploration and exploitation. Random walk via Lévy flight used by CS is more efficient in exploring the search space as its step length is heavy-tailed, and any large step is possible. On the other hand, CS has some sort of elitism and/or selection similar to that used in Harmony Search. Second, there are just two parameters to be fine-tuned in CS algorithm: population size and discovery probability (pa). The CS convergence rate is insensitive to the parameter pa. This also means that it is

not necessary to fine tune these parameters for a specific problem.

The effectiveness of this algorithm is demonstrated for test cases of three and six-generating units. The CS results are compared to six others population-based methods: Particle Swarm Optimization (PSO) [13], Shuffled Frog Leaping Algorithm (SFLA) [14], Bacterial Foraging Optimization (BFO) [15], Artificial Bee Colony (ABC) [16], Harmony Search (HS) [17] and Firefly Algorithm (FA) [18].

The remaining sections of this work are organized as follows: Section 2 describes the formulation of an ELD. Section 3 describes the CS algorithm. Section 4 presents the two case tests, the computational settings and analyzes the CS results when applied to case studies of ELDs with three and six-generating units and compared with the others six algorithms' results. Lastly, Section 5 outlines the conclusions.

2. Problem Formulation

The purpose of the economic load dispatch problem in electrical power system is to schedule the outputs of committed generating units to meet the consumer load demand at a minimal operating cost, satisfying the equality and inequality constraints imposed to the system.

The economic dispatch for the operation of electrical units is described by a multi-objective mathematical programming problem, which consists of minimizing the function that determines the fuel cost (objective function), finding an optimal generation profile, subject to satisfy the load power and the technical limits of operation of the groups.

Consider an electrical groups park with n generating units. The total fuel cost for power generation to be minimized is the sum of contributions of each generating units, which is given by:

$$\min \sum_{i=1}^n F_i(P_i) \quad (1)$$

where: F_i is the fuel cost function for the generation unit i (in \$/h) and P_i (in MW) is the real power output for this unit.

The fuel cost characteristics of each generation unit i is represented by a quadratic equation:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i, \quad (2)$$

subject to:

$$P_i^{\min} \leq P_i \leq P_i^{\max}, \quad (3)$$

where: a_i , b_i and c_i are the fuel cost coefficients of the unit i , and P_i^{\min} and P_i^{\max} are the minimum and maximum generation limits of the real power of unit i (in MW).

In this context, an equality constraint should be at-

tempted. The total generated power by the units must be equal to the sum of total load demand and total real power loss in the transmission lines, as follows:

$$\sum_{i=1}^n P_i - P_D - P_L = 0 \quad (4)$$

where: P_D is the total system real power demand (in MW); P_L is the overall system real power losses (in MW).

In the methodology of constant loss formula coefficients (loss coefficient method) or B-coefficients, the network losses are expressed as a quadratic function of the generators power outputs that can be approximated in the form:

$$P_L = \sum_i^n \sum_j^n B_{ij} P_i P_j + \sum_i^n B_{i0} P_i + B_{00} \quad (5)$$

where: B_{ij} are the elements of loss coefficient square matrix B , B_{i0} is the i -th elements of the loss coefficient vector and B_{00} is the loss coefficient constant.

The generation capacity inequality constraint related to real power generation limits of each unit is given by Equation (3), whereas the power balance equality constraint (*i.e.*, balance between demand and production) is represented by Equation (4).

The swarm optimization algorithms were applied to minimize the following objective function:

$$f = \sum_{i=1}^n F_i(P_i) + q_1 \left(\text{abs} \left(\sum_{i=1}^n P_i - P_D - P_L \right) \right) \quad (6)$$

where: q_1 is a positive constant to penalize the solutions that does not attend the power load balance.

This objective function was established to include not only the load distribution in the generating units with a lower cost but also to satisfy the equality constraint of the system.

3. Cuckoo Search Algorithm

Cuckoo search (CS) is inspired by some species of a bird family called cuckoo because of their special lifestyle and aggressive reproduction strategy. This algorithm was proposed by Yang and Deb [12]. The CS is an optimization algorithm based on the brood parasitism of cuckoo species by laying their eggs in the communal nests of other host birds, though they may remove others' eggs to increase the hatching probability of their own eggs. Some host birds do not behave friendly against intruders and engage in direct conflict with them. If a host bird discovers the eggs are not their own, it will either throw these foreign eggs away or simply abandon its nest and build a new nest elsewhere [19].

The CS algorithm contains a population of nests or eggs. Each egg in a nest represents a solution and a

cuckoo egg represents a new solution. If the cuckoo egg is very similar to the host's, then this cuckoo egg is less likely to be discovered; thus, the fitness should be related to the difference in solutions. The better new solution (cuckoo) is replaced with a solution which is not so good in the nest. In the simplest form, each nest has one egg. When generating new solutions $x^{(t+1)}$ for, say cuckoo i , a Lévy flight is performed:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus \text{Lévy}(\lambda), \quad (7)$$

where $\alpha > 0$ is the step size which should be related to the scales of the problem of interest. In most cases, we can use $\alpha = O(1)$. The product \oplus means entry-wise multiplications. Lévy flights essentially provide a random walk while their random steps are drawn from a Lévy distribution for large steps:

$$\text{Lévy} \sim u = t^{-\lambda}, (1 < \lambda \leq 3), \quad (8)$$

which has an infinite variance with an infinite mean. Here the consecutive jumps/steps of a cuckoo essentially form a random walk process which obeys a power-law step-length distribution with a heavy tail.

The rules for CS are described as follows:

- Each cuckoo lays one egg at a time, and dumps it in a randomly chosen nest;
- The best nests with high quality of eggs (solutions) will carry over to the next generations;
- The number of available host nests is fixed, and a host can discover a foreign egg with a probability $p_a \in [0, 1]$. In this case, the host bird can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.

The later assumption can be approximated by the fraction p_a of the n nests which are replaced by new ones (with new random solutions). With these three rules, the basic steps of the CS can be summarized as the pseudocode shown below:

- 1) Define the objective function $f(x)$, $x = (x_1, \dots, x_d)^T$.
- 2) Set n , p_a and $MaxGenerations$ parameters.
- 3) Generate initial population of n nests x_i ($i = 1, 2, \dots, n$).
- 4) Move a cuckoo (i) randomly by Lévy flights.
- 5) Evaluate the fitness F_i .
- 6) Randomly choose a nest (j) among n available nests.
- 7) If $F_i > F_j$ then replace j by the new solution.
- 8) Abandon a fraction p_a of worse nests and create the same fraction of new nests at new locations via Lévy flights.
- 9) Keep the best solutions (or nests with quality solutions).
- 10) Sort the solutions and find the best current solution.
- 11) If stopping criterion is not satisfied, increase gen-

eration number and go to step 4.

12) Postprocess results and find the best solution among all.

4. Experiments

CS has been applied to solve the ELD problems in two different test cases for investigating its optimization capability, where the objective function was limited within power ranges of the generating units and transmission losses are employed to demonstrate that were taken into account. Its performance was compared with six swarm optimization algorithm. We describe the test systems, the parameters' settings and the experimental results as follows.

4.1. Test Systems

The CS and the other swarm algorithms were validated with two test systems consisting of three and six-generation units. The ELD problem was solved to obtain the minimum cost for the generation units with transmission losses. The Equation (6) was used as objective function for this problem.

4.1.1. Case 1: Three-Generating Unit System

This case study consists of three-generating units. The coefficients of fuel cost and the capacities of the generation units are shown in **Table 1**. In this case, the load

$$B_{i0} = 10^{-3} \times [-0.3908 \quad -0.1297 \quad 0.7047 \quad 0.0591 \quad 0.2161 \quad -0.6635]$$

Table 1. Generator cost coefficients for the three-generating unit system.

Unit	a (\$/MW ²)	b (\$/MW)	c (\$)	P^{\min} (MW)	P^{\max} (MW)
1	0.008	7	200	10	85
2	0.009	6.3	180	10	80
3	0.007	6.8	140	10	70

Table 2. Generator cost coefficients for the six-generating unit system.

Unit	a (\$/MW ²)	b (\$/MW)	c (\$)	P^{\min} (MW)	P^{\max} (MW)
1	0.007	7	240	100	500
2	0.005	10	200	50	200
3	0.009	8.5	220	80	300
4	0.009	11	200	50	150
5	0.0080	10.5	220	50	200
6	0.0075	12	120	50	120

demand expected (P_D) to be determined is 150 MW.

However, the transmission loss coefficients matrix B is specified as:

$$B_{ij} = 10^{-2} \times \begin{bmatrix} 0.0218 & 0.0093 & 0.0028 \\ 0.0093 & 0.0228 & 0.0017 \\ 0.0028 & 0.0017 & 0.0179 \end{bmatrix}$$

$$B_{i0} = 10^{-3} \times [0.3 \quad 3.1 \quad 1.5]$$

$$B_{00} = 0.030523.$$

4.1.2. Case 2: Six-Generating Unit System

The six-generating unit system is presented here where the power system load demand (P_D) is 700 MW and the fuel cost coefficients are given in **Table 2**. Comparing to Case 1, the complexity and non-linearity of the ELD problem are augmented.

The loss coefficients in the power transmission line (matrix B) are given by:

$$B_{ij} = 10^{-4} \times \begin{bmatrix} 0.14 & 0.17 & 0.15 & 0.19 & 0.26 & 0.22 \\ 0.17 & 0.60 & 0.13 & 0.16 & 0.15 & 0.20 \\ 0.15 & 0.13 & 0.65 & 0.17 & 0.24 & 0.19 \\ 0.19 & 0.16 & 0.17 & 0.71 & 0.30 & 0.25 \\ 0.26 & 0.15 & 0.24 & 0.30 & 0.69 & 0.32 \\ 0.22 & 0.20 & 0.19 & 0.25 & 0.32 & 0.85 \end{bmatrix}$$

$$B_{00} = 0.056.$$

4.2. Algorithm's Settings

We tested each test system for each swarm optimization algorithm. For every test, we carried on 20 independent runs with 5000 cycles per each run. We printed out worst, best and mean results as well the standard deviation within the set of 20 runs. Simulations were done on Intel Core i7 2630QM mobile processor with 4GB of RAM on Windows 7 x 64 Ultimate Operating System and Matlab R2010a. The parameters' settings of each algorithm chosen by experimentation are cited below:

- **Particle Swarm Optimization (PSO):** P (particles) = 20, φ_1 (cognitive term) = 2, φ_2 (social term) = 2.
- **Shuffled Frog Leaping Algorithm (SFLA):** m (memeplexes) = 10, n (frogs) = 10, q (submemeplexes) = 2, S_{\max} (step) = 5, iN (evolutions) = 5.
- **Bacterial Foraging Optimization (BFO):** S (bacteria) = 20, N_c = 10, N_s = 4, N_{re} = 4, N_{ed} = cycles, p_{ed} = 0.25, $d_{attract}$ = 0.1, $w_{attract}$ = 0.2, $h_{repellant}$ = 0.1, $w_{repellant}$ = 10.
- **Artificial Bee Colony (ABC):** col (colony) = 20, BN

(employed bees) = 10, BC (onlookers) = 10, C_{max} = 100.

- **Harmony Search** (HS): HMS (harmony memory size) = 2, $HMCR$ (harmony memory considering rate) = 80, PAR (pitch adjusting rate) = 0.4.
- **Firefly Algorithm** (FA): n (fireflies) = 20, α (randomization factor) = 0.2, β_0 (attractiveness) = 1.0, γ (absorption coefficient) = 1.0.
- **Cuckoo Search** (CS): n (nests) = 20, p_a (discovery rate) = 0.25.

4.3. Experimental Results

The results of CS algorithm were compared to those reported using PSO, SFLA, BFO and ABC [11]. HS and FA were implemented in this work for comparing with CS. The experimental results of overall simulations are shown in **Table 3**, where standard deviation and mean, worst and best costs for both test power systems were achieved.

In all cases, CS outperformed the solution founded by the others evaluated algorithms, in terms of reaching lowest worst cost, lowest mean cost solution and lowest standard deviation. As indicated in **Table 3**, CS pre-

sented the best convergence results and strong stability.

The optimal dispatch of the units is given in **Table 4** for the three-generating unit system and in **Table 5** for the six-generating unit system, in which CS results are compared to ABC and FA methods. The **Tables 4** and **5** indicate the furnished power by each generating unit, the total generated power and the transmission losses for the best simulation.

It is clear from **Tables 4** and **5** that the total power obtained by CS is closed to the constraint of the power demand. In this context, these CS approach performed better than the ABC and FA methods in terms of reducing the power transmission losses in the test case 2, while FA did not satisfy the power balance equality constraint (Equation (4)). Although the power outputs for PSO, SFLA, BFO and HS were not exhibited in these tables, all these methods achieved the active power balance.

5. Conclusions

In this work, Cuckoo Search is proposed for solving economic load dispatch problems. The effectiveness of this algorithm is demonstrated for test cases consisting of three and six-generating units. The results of the Cuckoo

Table 3. Results for the seven swarm intelligence algorithms for minimizing the generation cost considering 20 runs.

	Case 1				Case 2			
	Mean cost (\$/h)	Standard deviation	Worst cost (\$/h)	Best cost (\$/h)	Mean cost (\$/h)	Standard deviation	Worst cost (\$/h)	Best cost (\$/h)
PSO	1609.13	8.231	1627.87	1600.60	8722.04	177.652	8912.16	8401.45
SFL	1602.06	1.519	1607.62	1600.67	8479.49	54.781	8604.29	8419.78
BFO	1604.28	3.1993	1611.35	1600.02	8571.91	127.85	8909.85	8428.69
ABC	1607.37	11.676	1620.60	1600.51	8457.16	57.726	8610.28	8372.27
HS	1610.10	9.415	1629.18	1600.58	8541.72	99.531	8778.37	8398.06
FA	1617.34	10.746	1633.57	1600.47	8631.82	176.83	9082.00	8388.45
CS	1600.46	2.7e⁻⁶	1600.46	1600.46	8356.06	0.0008	8356.06	8356.06

Table 4. Results for the best simulations with three-generating units system.

Power outputs	CS	ABC	FA
Unit 1 (MW)	33.490	33.049	32.729
Unit 2 (MW)	64.116	61.764	63.843
Unit 3 (MW)	55.126	57.872	56.151
P_L (MW)	2.73	2.70	2.72
P_D (MW)	150	150	150
ΣP_i (MW)	152.73	152.69	152.72
Cost (\$)	1600.46	1600.51	1600.47

Table 5. Results for the best simulations with six-generating units system.

Power outputs	CS	ABC	FA
Unit 1 (MW)	324.113	323.043	293.312
Unit 2 (MW)	76.859	54.965	79.546
Unit 3 (MW)	158.094	147.354	123.334
Unit 4 (MW)	50.000	50.000	69.700
Unit 5 (MW)	51.963	85.815	79.546
Unit 6 (MW)	50.000	50.233	63.778
P_L (MW)	11.03	11.40	11.44
P_D (MW)	700	700	700
ΣP_i (MW)	711.03	711.40	709.22
Cost (\$)	8356.06	8372.27	8388.45

Search are compared with that of other six swarm intelligence algorithms. Although in this work there are not methodological innovations, the comparison among the swarm methods is very interesting for potential real applications.

After contrasting the simulation results with the other algorithms, it is obviously seen that Cuckoo Search gives better results than other algorithms. Cuckoo Search is easy to implement and capable of finding feasible near global optimal solution.

In addition, the results substantiate the robustness, precise convergence and efficiency of this optimization algorithm. The main advantage of Cuckoo Search is a good ability for finding the solution. From the results obtained it can be concluded that Cuckoo Search is a competitive technique for solving complex nonsmooth optimization problems in power system operation.

6. Acknowledgements

The authors would like to thank Fundação de Amparo à Pesquisa do Estado de São Paulo for the financial support (Process FAPESP No 2011/08108-0).

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