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Economic Dispatch of Wind-Thermal Power System using Modified Cuckoo Search Algorithm

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--ABSTRACT--
This paper presents a modified cuckoo search algorithm (MCSA) which is improved version of cuckoo search algorithm (CSA) for solving the economic dispatch (ED) problem considering wind power. Many practical constraints of generators such as ramp rate limits, prohibited operating zones and transmission loss are considered. The modification involves the addition of information exchange between the top eggs, or the best solutions. The effectiveness of the proposed approach has been tested on 6 generator system with and without wind power. The results show that performance of the proposed approach reveal the efficiently and robustness when compared results of other optimization algorithms reported in literature.
Keywords *- Modified cuckoo search algorithm, economic dispatch, wind power, ramp rate limits, prohibited operating zones.*

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I. INTRODUCTION

The Economic Dispatch (ED) problem is one of the fundamental issues in power system planning, operation and control, where the total required load is distributed among the generation units in operation. The main objective of ED problem is to minimizing total generation cost while satisfying load and operational constraints. Traditionally, fuel cost function of a generator is represented by single quadratic function. But a quadratic function is not able to show the practical behavior of generator. For modeling of the practical cost function behavior of a generator, a non-convex curve is used in literature. The ED problem is a non-convex and nonlinear optimization problem. Due to ED complex and nonlinear characteristics, it is hard to solve the problem using classical optimization methods. Most of classical optimization techniques such as lambda iteration method, gradient method, Newton's method, linear programming, Interior point method and dynamic programming have been used to solve the basic economic dispatch problem [1]. These mathematical methods require incremental or marginal fuel cost curves which should be monotonically increasing to find global optimal solution. In reality, however, the input-output characteristics of generating units are non-convex due to valve-point loadings and multi-fuel effects, etc. Also, there are various practical limitations in operation and control such as ramp rate limits and prohibited operating zones, etc. Therefore, the practical ED problem is represented as a non-convex optimization problem with equality and inequality constraints, which cannot be solved by the traditional mathematical methods. Dynamic programming (DP) method [2] can solve such types of problems, but it suffers from so-called the curse of dimensionality.

Renewable energy is energy resource that comes from sustainable natural processes, such as energy from wind energy, solar energy, hydropower, biomass and geothermal energy. Renewable energy began to attract the attention of people and policy makers as an alternative energy resource after the world oil crisis in 1973. The use of renewable energy then rapidly developed when the United Nations Framework Convention on Climate Change (UNFCCC) was formed by the United Nations as a movement to reduce gas greenhouse. The main cause of climate change is electricity production activities which are dominated by coal-fired power plants and natural gas power plants which account for around 30% of total gas emissions that cause global warming. Wind energy is a clean and rapidly growing renewable energy resources. They have shown great prospects in decreasing fuel consumption as well as reducing pollutants emission. However, the expected wind power is difficult to predict accurately, primarily due to the intermittent nature of the wind speed, coupled with the highly non-linear wind energy conversion. In order to adjust unforeseeable nature of the wind power, planned productions and uses in electricity market must be improved during the real operation of the power system. Due to the intermittent characteristic of wind power, ED is very suited for formulate the problem of optimal scheduling of generating units by including wind power. Until now, very limited research has been done to overcome the problem of ED with wind power [3-6].

Over the past few decades, as an alternative to the conventional mathematical approaches, many salient methods have been developed for ED problem such as genetic algorithm (GA) [7], improved tabu search (TS) [8], simulated annealing (SA) [9], neural network (NN) [10], evolutionary programming (EP) [11, 12], particle swarm optimization (PSO) [13, 14], differential evolution (DE) [15], and gravitational search algorithm (GSA) [16], biogeography-based optimization (BBO) [17].

Recently, a new meta-heuristic search algorithm, called cuckoo search algorithm (CSA) [18, 19], has been developed by Yang and Deb. In this paper, modified cuckoo search algorithm (MCSA) which is improved version of CSA has been used to solve the ED problem considering ramp rate limits, prohibited operating zones, and transmission loss. Feasibility of the proposed method has been demonstrated on 6 generator system with and without wind power. The results obtained with the proposed method were analyzed and compared with CSA and other optimization results reported in literature.

II. PROBLEM FORMULATION

The main objective of an ED problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying equality and inequality constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator. For a given power system network, the problem may be described as optimization (minimization) of total fuel cost as defined by (1) under a set of operating constraints.

$$F_T = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i \right) \tag{1}$$

where F_T is total fuel cost of generation in the system (\$/hr), a_i, b_i, and c_i are the cost coefficient of the *i*-th generator, P_i is the power generated by the *i*-th unit and n is the number of generators.
The cost is minimized subjected to the following constraints:

2.1. Active Power Balance Equation

For power balance, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total line loss.

$$\sum_{i=1}^{n} (P_i + P_W) = P_D + P_{Loss} \tag{2}$$

where P_W is power output of wind farm, P_D is the total load demand and P_{Loss} is total transmission losses. The transmission losses P_{Loss} can be calculated by using ***B*** matrix technique and is defined by (3) as,

$$P_{Loss} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \tag{3}$$

where B_{ij} is coefficient of transmission losses and the B_{0i} and B_{00} is matrix for loss in transmission which are constant under certain assumed conditions.

2.2. Minimum and Maximum Power Limits

Generation output of each generator should lie between minimum and maximum limits. The corresponding inequality constraint for each generator is

$$P_i^{\min} \le P_i \le P_i^{\max} \quad \text{for } i = 1, 2, \cdots, n \tag{4}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum outputs of the *i*-th generator, respectively.

2.3. Ramp Rate Limits

The actual operating ranges of all on-line units are restricted by their corresponding ramp rate limits. The ramp-up and ramp-down constraints can be written as (5) and (6), respectively.

$$P_i(t) - P_i(t-1) \le UR_i \tag{5}$$

$$P_i(t-1) - P_i(t) \le DR_i \tag{6}$$

where $P_i(t)$ and $P_i(t\text{-}1)$ are the present and previous power outputs, respectively. UR_i and DR_i are the ramp up and ramp-down limits of the *i*-th generator (in units of MW/time period).

To consider the ramp rate limits and power output limits constraints at the same time, therefore, equations (4), (5) and (6) can be rewritten as follows:

$$\max\{P_i^{\min}, P_i(t-1) - DR_i\} \le P_i(t) \le \min\{P_i^{\max}, P_i(t-1) + UR_i\} \tag{7}$$

2.4. Prohibited Operating Zones

In practical operation, the entire operating range of a generating unit is not always available due to physical operation limitations. Units may have prohibited operating zones due to robustness in the shaft bearings caused by the operation of steam values or to faults in the machines themselves or the associated auxiliaries, such as boilers, feed pumps etc. Such faults may lead to instability in certain ranges of generator power output. Therefore, for units with prohibited operating zones, there are additional constraints on the unit operating range as follows:

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^l \\ P_{i,k-1}^u \le P_i \le P_{i,k}^l, \quad k = 2,3,\ldots,pz_i \\ P_{i,pz_i}^u \le P_i \le P_i^{\max}, \ i = 1,2,\ldots,n_{pz} \end{cases} \tag{8}$$

where $P_{i,k}^l$ and $P_{i,k}^u$ are the lower and upper boundary of prohibited operating zone of unit *i*, respectively. Here, pz_i is the number of prohibited zones of unit *i* and n_{pz} is the number of units which have prohibited operating zones.

III. 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 [18]. 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 for $x^{(t+1)}$, say cuckoo *i*, a Lévy flight is performed:

$$x_i^{(t+1)} = x_i^t + \alpha \oplus \text{Lévy}\,(\lambda) \tag{9}$$

where α > 0 is the step size which should be related to the scales of the problem of interest. In most cases, we can use α = 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:

$$\text{Lévy} \sim \text{u} = \text{t}^{-\lambda}, (1 < \lambda \le 3) \tag{10}$$

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 pseudo-code shown bellows,

1) Define the objective function $f(x), x = (x_1, \cdots, x_d)^T$
2) Set *n*, p_a, and Max Generation parameters
3) Generate initial population of *n* available nests
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 $f_i > f_j$ the 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 location 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 criteria is not satisfied, increase generation number and go to step 4
    Postprocess results and find the best solution among all.

IV. MODIFIED CUCKOO SEARCH ALGORITHM

Modified Cuckoo Search algorithm (MCSA) is the modified version of cuckoo search algorithm, which performs superior to the cuckoo search (CS), PSO and DE. In MCSAs two parameters are to be adjusted, the population size n, and p_d. Once n is set, p_d controls the elitism, which needs to be adjusted. Due to small number of parameters, modified cuckoo search algorithm is less complex and more generic [20].

In modified version of cuckoo search algorithm (CSA), two modifications are done. The first modification is made to the Lévy flight step size α. In CSA, the value of α is 1 and is constant, whereas in MCSA if the number of generations increase the value of α is reduced. In the MCSA, a portion of the eggs with the best fitness (quality) are put into a group of top eggs [20].

Initially, the value of Lévy flight step size A = 1 was selected and, at each generation, a new value of Lévy flight step size is calculated by using $\alpha = A/\sqrt{G}$, where G is the generation number. This exploratory search is carried out only on the fraction of nests to be abandoned [20]. Both, cuckoo search and modified cuckoo search algorithm use random step sizes.

Computational steps for modified cuckoo search algorithm can be summarized as the pseudo-code shown bellows:

Step 1: Initialize the population of cuckoo with eggs.

Step 2: Calculate the fitness of function $F_i = f(x_i)$, i=1, 2, ..., n, for each generation until the no. of objective evaluation is less than the maximum no. of evaluation.

Step 3: Arrange all the fitness function values in the order of their fitness.

Step 4: After the evaluation, calculate the number of nests to be abandoned *na*.

Step 5: Calculate the Lévy flight step size by using $\alpha = A/\sqrt{G}$. Generate a new egg by performing the Lévy flight from a randomly selected position of an egg. If the generated new egg is better than the other randomly selected egg than this egg is moved to new position.

Step 6: The random search of Lévy flight is controlled by multiplying it with α and now $\alpha = A/G^2$ is to explore the abandoned nests.

Step 7: The new generated egg is randomly chosen. The egg having the best fitness are grouped in one and from these a second egg is randomly taken and a new egg is generated along the distance which is calculated using,

$$dx = \left| x_i - x_j \right| / \varphi$$

The distance is such calculated that the nest is moved towards the worst to the best position of an egg.

Step 8: The best nest is being selected as the best objective value so far.

V. SIMULATION RESULTS

In order to demonstrated the performance of the proposed method a 6-units test system with considering power loss, ramp rate limits and prohibited operating zones are considered. The proposed algorithm is applied to the test systems with and without considering wind power. The higher output of wind-powered generator is 30 MW [3]. The total load demand on the system is 1263 MW. The parameters of all generating units are presented in Table 1 and Table 2 [13], respectively.

Table 1: Cost coefficients and unit operating limits

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a	b	c
1	100	500	0.0070	7.0	240
2	50	200	0.0095	10.0	200
3	80	300	0.0090	8.5	220
4	50	150	0.0090	11.0	200
5	50	200	0.0080	10.5	220
6	50	120	0.0075	12.0	190

Table 2: Ramp rate limits and prohibited operating zones

Unit	P_i^0 (MW)	UR_i (MW/h)	DR_i (MW/h)	Prohibited zones (MW)
1	440	80	120	[210, 240] [350, 380]
2	170	50	90	[90, 110] [140, 160]
3	200	65	100	[150, 170] [210, 240]
4	150	50	90	[80, 90] [110, 120]
5	190	50	90	[90, 110] [140, 150]
6	110	50	90	[75, 85] [100, 105]

The transmission losses are calculated by ***B*** matrix loss formula which for 6 generator system is given as:

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_{0i} = 10^{-3} \times \left[-0.3908 \ -0.1297 \ 0.7047 \ 0.0591 \ 0.2161 \ -0.6635\right]$$

$$B_{00} = 0.056$$

The obtained result for 6 generator system using the CSA and MCSA method are given in Table 3 and the results are compared with other methods reported in literature, including BBO, GA, PSO and IDP. It can be observed that MCSA can get total fuel cost of 15442.3928 ($/h) and total loss of 12.3939 (MW), which is the best solution among all the methods. Note that the outputs of the generators are all within the generator's permissible output limit. The cost convergence characteristic of 6 generator system obtained from CSA and MCSA is shown in Figure 1. It is seen that the proposed method reaches convergence faster than the CSA method.

Table 3: Comparison of the best results of each method (P_D = 1263 MW)

Unit Output	BBO [17]	GA [21]	PSO [21]	IDP [21]	CSA	MCSA
P1 (MW)	447.3997	474.8066	447.4970	450.9555	445.5731	447.3977
P2 (MW)	173.2392	178.6363	173.3221	173.0184	172.8935	173.2026
P3 (MW)	263.3136	262.2089	263.0594	263.6370	264.4220	263.3661
P4 (MW)	138.0060	134.2826	139.0594	138.0655	138.5840	138.9418
P5 (MW)	165.4104	151.9039	165.4761	164.9937	166.9367	165.3789
P6 (MW)	87.0797	74.1812	87.1280	85.3094	87.0080	87.1067
Total generation (MW)	1275.4460	1276.0217	1275.9584	1275.9794	1275.4172	1275.3939
Total fuel cost ($/h)	15443.09	15459	15450	15450	15442.4529	15442.3928
Total loss (MW)	12.446	13.0217	12.9584	12.9794	12.4172	12.3939

In Table 4, ED is carried out by considering thermal as well as wind power simultaneously. From the Table 4, it is understood that the cost and transmission losses are significantly reduced with the integration of wind power in to the system. The cost convergence characteristic of 6-generator system with wind power is given in Figure 2.

Table 4: Simulation results for 6-generator system with and without wind power using MCSA

Unit Output	Without wind power	With wind power
P1 (MW)	447.3977	443.4757
P2 (MW)	173.2026	170.2548
P3 (MW)	263.3661	259.4349
P4 (MW)	138.9418	136.2384
P5 (MW)	165.3789	161.0422
P6 (MW)	87.1067	83.9991
Total generation (MW)	1275.3939	1254.4452
Wind power produced (MW)	-	20.5451
Total fuel cost ($/h)	15442.3928	15205.9913
Total loss (MW)	12.3939	11.9903

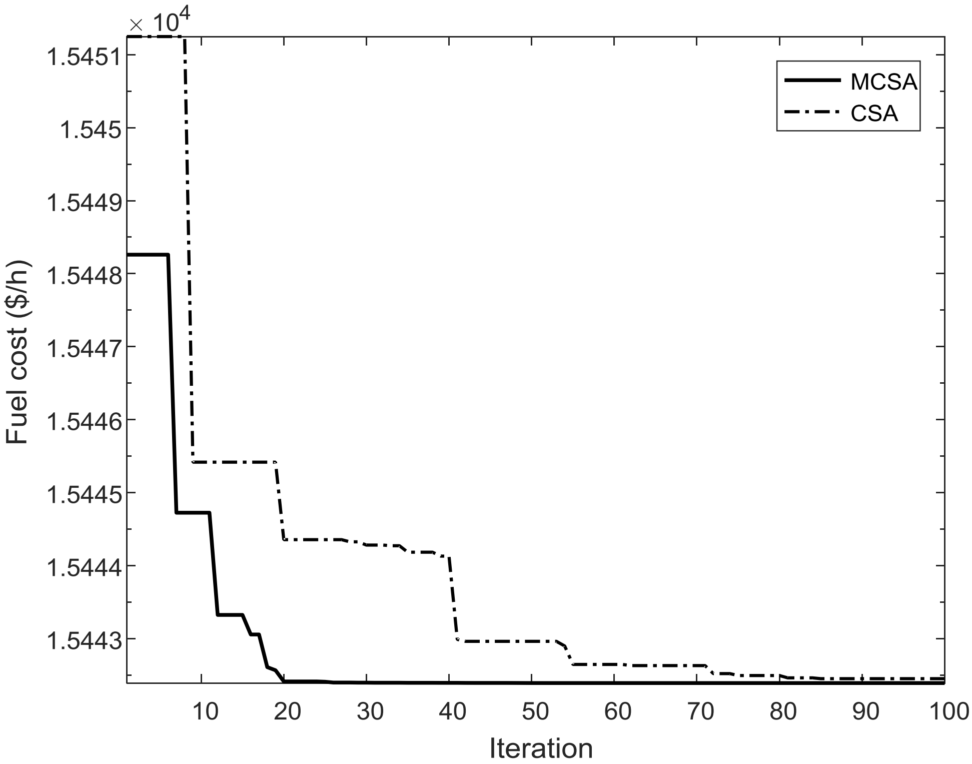

Figure 1. Cost convergence characteristic of 6-generator system

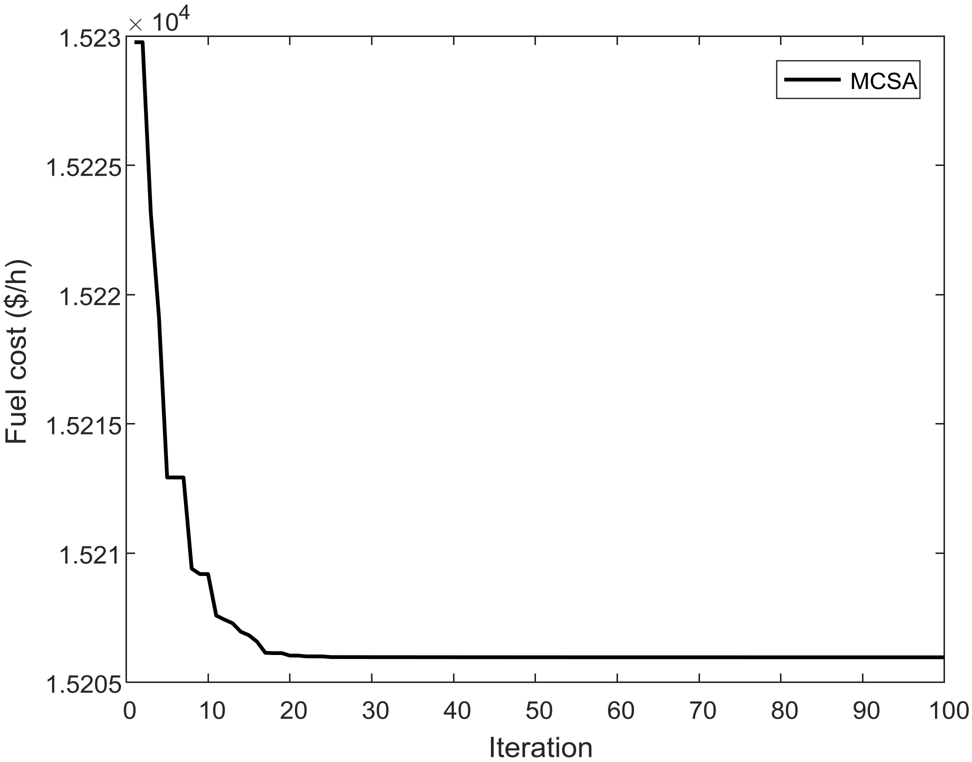

Figure 2. Cost convergence characteristic of 6-generator system with wind power

VI. CONCLUSION

In this paper, a modified cuckoo search algorithm (MCSA) has been successfully applied for solving economic dispatch problem. Different constraints such as the ramp rate limits, prohibited operating zones and transmission loss are taken into consideration to solve the ED problem with and without wind power. Modified cuckoo search algorithm (MCSA) is a new gradient free optimization algorithm. MCSA shows a high convergence rate, able to outperform other optimisers. The proposed technique has provided the global solution in the 6 generator systems and the better solution than the previous studies reported in literature. It is concluded that MCSA performs well when applied to engineering problems.

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