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# Optimal Generation Coordination of Hydrothermal System

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***Abstract***

*This paper presents the use of an enhanced version of conventional cuckoo search algorithm (ECSA) for solving optimal generation coordination of hydrothermal system where the objective is to minimize both fuel cost and emission, and the hydro model is represented as a quadratic function of water discharge with respect to generation. The ECSA method is built for the optimal operation based on several modifications on conventional Cuckoo search algorithm (CSA). In the ECSA method, by evaluating the fitness of all initial eggs they are divided into two parts including the high quality one with lower fitness value and bad quality one with higher fitness value. The ECSA is tested on several systems and obtained results from the ECSA are compared those from other methods. The comparison reveals that the ECSA is so efficient for the considered problem.*

***Keywords**: Enhanced Cuckoo search algorithm, economic dispatch, emission dispatch, economic emission dispatch*

## 1. Introduction

The main task of the optimal generation coordination of hydrothermal system (OGC-HTS) problem is to determine the optimal power generation of the available thermal and hydro power plants so as the total fuel cost of thermal units over a schedule time is minimized satisfying both equality and inequality constraints such as the quantity of available water, power balance, and upper and lower limits on generations. In addition, a large amount electric power in the world supplying to load demand is mainly generated by thermal plants using oil, coal or natural gases. Therefore, several contaminants such as nitrogen oxides ($NO_x$), sulphur dioxide ($SO_2$), and carbon dioxide ($CO_2$) have been released into the atmosphere due to the process of electricity generation from the thermal units [1]. In addition to the total fuel cost of thermal units, another objective of the gaseous emission should be also added to the OGC-HTS problem and a multi-objective OGC-HTS problem is formulated. Therefore, the multi-objective OGC-HTS (MO-OGS-HTS) problem is more complex than the conventional one since it needs to find a set of non-dominated solutions for determining the best compromise solution which is considered as the most reasonable one for the acceptable trade-off between fuel cost and emission objectives.

Recent years, many meta-heuristic algorithms have been successfully and widely applied to the MO-OGS-HTS problem such as particle swarm optimization (PSO) and gamma based method ($\gamma$-PSO) in [2], simulated annealing-based goal-attainment (SA-BGA) method [3] and Non-dominated sorting genetic algorithm-II (NSGA-II) [3], improved genetic algorithm, and multiplier updating and the $\varepsilon$-constraint technique (IGA-MU) [4] in addition to augmented Lagrange Hopfield network (ALHN) known as an

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artificial intelligence algorithm [5]. Among the methods, the ALHN method is not able to implement on systems with nonconvex fuel cost function of thermal units. GA is one of the earliest artificial intelligence methods which can deal with problem with complex constraints; however, it is time consuming to obtain optimal solution. Therefore, an improved version of the GA, NSGA-II was developed in [2] to tackle the disadvantage. On the contrary, PSO is faster than GA but it also copes with local optimal solution. In general, the meta-heuristic algorithm can find near optimum solution for non-convex optimization problems with non-differentiable objective and constraints. However, since the artificial intelligence based methods are generally based on the random search of a population in the problem space, they need to be run several times to obtain the best solution.

Cuckoo search algorithm (CSA) was first developed by Yang and Deb in 2009 [6] inspired from the cuckoo bird's reproduction behavior. The CSA method is superior to other methods such as GA and PSO when applied to benchmarked functions [6]. However, Walton et al. in [7] have pointed out that the conventional CSA cannot be fast for large size systems. In the ECSA, all the initial eggs are divided into two parts consisting of high quality eggs part and bad quality eggs part. ECSA has been demonstrated superior to CSA as applied to short-term fixed head hydrothermal scheduling problem [8].

In this paper, the ECSA method is proposed for solving the MO-OGS-HTS problem considering power losses in transmission systems and valve point loading effects in fuel cost function of thermal units. For implementation of the ECSA, thermal generations and water discharges as elements in each nest are used. The proposed ECSA method have been tested on three systems with quadratic fuel cost function and four objectives including three emission objectives and one fuel cost objective. The obtained results from the proposed ECSA have been compared to those from other methods available in the literature.

## 2. Problem Formulation

The mathematical formulation the of the MO-GCO-HTS problem consisting of $N_1$ thermal units and $N_2$ hydro units scheduled in $M$ time subintervals with $t_m$ hours for each is formulated as follows.

### 2.1. Fuel Cost Objective

The fuel cost function of thermal units considering valve point loading effects is represented as follows:

$$F_1 = \sum_{m=1}^{M} \sum_{i=1}^{N_1} t_m \left\{ a_{si} + b_{si} P_{si,m} + c_{si} P_{si,m}^2 + \left| e_{si} \times \sin\left( f_{si} \times \left( P_{si}^{\min} - P_{si,m} \right) \right) \right| \right\} \tag{1}$$

where $a_{si}$, $b_{si}$, $c_{si}$, $e_{si}$, $f_{si}$ are fuel cost coefficients of thermal plant $i$; $P_{si,m}$ is power output of thermal unit $i$ at subinterval $m$; and $P_{si}^{min}$ is the minimum power output of thermal unit $i$.

### 2.2. Emission Objective

Mathematically, each gaseous emission is represented by a quadratic function as follows:

$$F_2 = \sum_{m=1}^{M} \sum_{i=1}^{N_1} t_m \left( \alpha_{si} + \beta_{si} P_{si,m} + \gamma_{si} P_{si,m}^2 \right) \tag{2}$$

In addition to the quadratic function representation of emission gas, the amount of emission from each thermal unit can be also expressed in form of a quadratic and exponential function as follows:

$$F_2 = \sum_{m=1}^{M} \sum_{i=1}^{N_1} t_m \left[ \alpha_{si} + \beta_{si} P_{si,m} + \gamma_{si} P_{si,m}^2 + \eta_{si} \exp(\delta_{si} P_{si,m}) \right] \quad (3)$$

where $\alpha_{si}$, $\beta_{si}$, $\gamma_{si}$, $\eta_{si}$, and $\delta_{si}$ are emission coefficients of thermal unit $i$.

### 2.3. System and Unit Constraints

#### 2.3.1. Load Demand

The total power generation from thermal and hydro units must satisfy the load demand and power losses in transmission lines represented by:

$$\sum_{i=1}^{N_1} P_{si,m} + \sum_{j=1}^{N_2} P_{hj,m} - P_{L,m} - P_{D,m} = 0\ ;\ m = 1, \ldots, M \quad (4)$$

where the power losses in transmission lines are calculated using Kron's formula as follows:

$$P_{Lm} = \sum_{i=1}^{N_1+N_2} \sum_{j=1}^{N_1+N_2} P_{im} B_{ij} P_{jm} + \sum_{i=1}^{N_1+N_2} B_{0i} P_{im} + B_{00}\ ;\ m = 1, \ldots, M \quad (5)$$

where $P_{hj,m}$ is power output of hydro unit $j$ at subinterval $m$; $P_{D,m}$ and $P_{L,m}$ are total system load demand and total transmission loss at subinterval $m$, respectively; and $B_{ij}$, $B_{0i}$, $B_{00}$ are matrix coefficients for transmission power losses.

#### 2.3.2. Water Availability Constraints

The total water discharge for each hydro unit during the scheduled period is limited by the available amount of water for that unit as follows:

$$\sum_{m=1}^{M} t_m q_{j,m} = W_j\ ;\ j = 1, \ldots, N_2 \quad (6)$$

where $q_{j,m}$ is the rate of water flow via turbine of hydro plant $j$ in interval $m$.

$$q_{j,m} = a_{hj} + b_{hj} P_{hj,m} + c_j P_{hj,m}^2 \quad (7)$$

where $a_{hj}$, $b_{hj}$, $c_{hj}$ are water discharge coefficients of hydro unit $j$ and $W_j$ is the volume of water available for generation by hydro plant $j$ during the scheduled period.

#### 2.3.3. Generator Operating Limits

The power output of thermal and hydro units is limited between their upper and lower limits:

$$P_{si,\min} \le P_{si,m} \le P_{si,\max}\ ;\ i = 1, 2, \ldots, N_1\ ;\ m = 1, 2, \ldots, M \quad (8)$$

$$P_{hj,\min} \le P_{hj,m} \le P_{hj,\max}\ ;\ j = 1, 2, \ldots, N_2\ ;\ m = 1, 2, \ldots, M \quad (9)$$

where $P_{si,max}$, $P_{si,min}$ are maximum and minimum power outputs of thermal unit $i$, respectively and $P_{hj,max}$, $P_{hj,min}$ are maximum and minimum power outputs of hydro plant $j$, respectively.

## 3. ECSA for MO-OGC-HTS Problem

### 3.1. Calculation of Power Output for Slack Thermal and Hydro Units

The hydro generation is obtained as below [8]:

 

$$P_{hj,m} = \frac{-b_{hj} \pm \sqrt{b_{hj}^2 - 4c_{hj}(a_{hj} - q_{j,m})}}{2c_{hj}}; m = 1, \ldots, M; j = 1, 2, \ldots, N_2 \quad (10)$$

where $\left(b_{hj}^2 - 4c_{hj}(a_{hj} - q_{j,m})\right) \geq 0$

Suppose that a set of the power outputs of ($N_1$ -1) thermal units are known, the power output of the slack thermal unit 1 is calculated as follows [8]:

$$P_{s1,m} = P_{D,m} + P_{L,m} - \sum_{i=2}^{N_1} P_{si,m} - \sum_{j=1}^{N_2} P_{hj,m} \quad (11)$$

### 3.2. Implementation of ECSA for MO-GCO-HTS Problem

The proposed ECSA method is implemented for solving the MO-GCO-HTS problem as follows.

#### 3.4.1. Initialization

Similar to other meta-heuristic algorithms, the proposed ECSA has a population of $N_p$ host nests representing $X_d$ ($d$ = 1, 2, …, $N_p$) containing $P_{si,m,d}$ ($i = 2, \ldots, N_1; m=1, \ldots, M$) and $q_{j,m,d}$ ($j=1,.., N_2; m=1,\ldots, M-1$), where $P_{si,m,d}$ is the power output of thermal unit $i$ at subinterval $m$ corresponding to nest $d$ and $q_{j,m,d}$ is the water discharge of hydro unit $j$ at subinterval $m$ corresponding to nest $d$. Therefore, vector $X_d$ of nest $d$ is represented in detail by $X_d = [P_{s2,m,d}, P_{s3,m,d}, \ldots, P_{sN_1,m,d}, q_{1,m,d}, q_{2,m,d}, \ldots, q_{N_2,m.d}]$, which includes the thermal units from 2 to $N_1$ for $M$ subintervals and water discharges for hydro units from 1 to $N_2$ for the first ($M$-1) subintervals. Consequently, nest $d$ only contains thermal units from 2 to $N_1$ at subinterval $M$. Certainly, the upper and lower limits of each nest are respectively $X_{dmin}=[P_{simin}, q_{jmin}]$ and $X_{dmax}=[P_{simax}, q_{jmax}]$.

The power output of the thermal units and water discharge of hydro units in the $N_p$ nests are randomly initialized satisfying $P_{si,m,d} \leq P_{si,max}$ and $q_{j,min} \leq q_{j,m,d} \leq q_{j,max}$ as follows:

$$X_d = X_{d\min} + rand * (X_{d\max} - X_{d\min}); \quad d = 1, \ldots, Np \quad (12)$$

where $rand$ is uniformly distributed random numbers in [0,1].

Based on the initialized nests, the fitness function to be minimized corresponding to each nest for the considered problem is calculated as:

$$FT_d = \sum_{m=1}^{M} \sum_{i=1}^{N_1} \left( w * F_1(P_{si,m,d}) + (1-w) * F_2(P_{si,m,d}) \right) + K_s \sum_{m=1}^{M} (P_{s1,m,d} - P_{s1}^{\lim})^2 + K_q \sum_{j=1}^{N_2} (q_{j,M,d} - q_j^{\lim})^2 \quad (13)$$

where $0 \leq w \leq 1$ is weighting factor for combination of objectives [9]; $K_s$ and $K_q$ are penalty factors; $P_{s1,m,d}$ is obtained by (11) and $q_{j,M,d}$ is the water discharge of hydro plant $j$ at the subinterval $M$ calculated by (14); $P_{s1}^{lim}$ and $q_j^{lim}$ are the limits for the slack thermal unit and the slack water discharge *[8]*.

#### 3.4.2. Generation of New Solution via Lévy Flights

All the eggs are divided into two parts, namely *Xbest_discard$_d$* in good quality part and *Xbest_nodiscard$_d$* in bad quality part. One nest randomly picked among the *Xbest_nodiscard$_d$* nests is called *Xbest_nodiscard$_r$*. The nest corresponding to the best fitness function in (13) is set to the best nest *Gbest* among all nests in the population.

a) Generation of new solution for the bad quality part

The first modification is for generating the new solution in the bad quality part ($d$ = *Notop*+1,…, $N_d$, where *Notop* is the number of nests in the good quality part ) using Mantegna's algorithm as follows:

 

$$Xdiscard_d^{new} = Xbest\_discard_d + \alpha \times rand \times \Delta Xdiscard_d^{new} \tag{14}$$

where the step size $\alpha = A_0 / \sqrt{G}$ is determined and $\Delta Xdiscard_d^{new}$ is obtained as follows:

$$\Delta Xdiscard_d^{new} = v \times \frac{\sigma_x(\beta)}{\sigma_y(\beta)} \times (Xbest\_discard_d - Gbest); \tag{15}$$

*Generation of new solution for the good quality part*

The new solution is determined using Mantegna's algorithm as follows:

$$Xnodiscard_d^{new} = Xbest\_nodiscard_d + \alpha \times rand \times \Delta Xnodiscard_d^{new} \tag{16}$$

where $\alpha$ and $\Delta Xnodiscard_d^{new}$ are updated step size and an increased value [8].

For the newly obtained solution, its lower and upper limits should be satisfied according to the unit's limits:

$$X_d = \begin{cases} X_{d\max} & \text{if } X_d > X_{d\max} \\ X_{d\min} & \text{if } X_d < X_{d\min} \\ X_d & \text{otherwise} \end{cases} \tag{17}$$

The fitness function value of the new egg is calculated using (13) and then compared to that from the previous egg. The egg with better fitness function value is considered as the new solution.

### 3.4.1. Alien Egg Discovery and Randomization

The second new solution generation is carried out by the following equation

$$X_d^{dis} = \begin{cases} Xbest_d + rand \begin{bmatrix} randp_1(Xbest_d) \\ -randp_2(Xbest_d) \end{bmatrix} & \text{if rand} < \text{Pa} \\ Xbest_d & otherwise \end{cases} \tag{18}$$

where $randp_1(Xbest_d)$ and $randp_2(Xbest_d)$ are the random perturbation for positions of the nests in $Xbest_d$.

For the newly obtained solution, its lower and upper limits should be also satisfied. The value of the fitness function in (13) is recalculated and the nest corresponding to the best fitness function is set to the best nest *Gbest* of the population.

## 4. Numerical Results

The proposed ECSA and conventional CSA methods have been tested on three systems where the first system has one hydropower plant and one thermal plant, and the second system has two hydropower plants and one thermal plant and the fourth system has two hydropower plants and two thermal plants. The three systems are scheduled in twenty four subintervals with one hour for each. Both the methods CSA and ECSA are run fifty independent trials for each case on a 1.8 GHz PC with 4 GB of RAM.

The emission data of the systems is from [10] and the rest of data is from [1]. The two methods of CSA and ECSA are implemented to for obtaining the optimal solution for the cases of economic dispatch ($w$ = 1), emission dispatch ($w$ = 0), and combined economic emission dispatch ($w$ = 0.5). The number of nests and the maximum number of iterations for the three systems are given in Table 1 whereas the probability of alien eggs to be abandoned for both CSA and ECSA is tuned in range from 0.1 to 0.9 with a step of 0.1. It is obviously seen from Table 1, the number of nests set to ECSA is smaller than that set to CSA. The best results obtained by the CSA and ECSA are compared to those from other methods given in Table 2 corresponding to economic dispatch, in Table 3 corresponding to emission dispatch and in Table 4 corresponding to combined economic and emission dispatch. Obviously, the ECSA has approximate solution to CSA for economic dispatch of all the three systems; however, at the emission dispatch, the proposed ECSA can search better solutions than CSA for the three systems due to less emission. There is a conflict between the comparison of fuel cost and emission at the combined economic and emission dispatch at Table 4 when evaluate the performance of the CSA and ECSA. Clearly, the ECSA obtain less fuel cost and higher emission than CSA for three systems. Consequently, it is sated that the ECSA is more effective than CSA. As compared to three other methods in [2] such as Lamda-gamma method (LGM), PSO and γ-PSO, the ECSA is superior to three of them at economic dispatch since the ECSA obtain better fuel cost for systems 1 and 3 and worse cost only at system 2. Furthermore, the ECSA obtains better both emission for emission dispatch, and fuel cost and emission for compromise case than the three methods. The comparison of execution time among these methods is reported in Table 5. Obviously, the ECSA is slower than other methods; however, the LGM and γ-PSO in [2] are the family of the deterministic methods which cannot deal with non-differential function and the PSO is much less efficient than the ECSA. There is no computer reported for the methods in [2].

**Table 1. The Telection of CSA and ECSA Control Parameters**

| System | CSA | | ECSA | |
|---|---|---|---|---|
| | Np | Gmax | Np | Gmax |
| 1 | 10 | 1,000 | 8 | 1,000 |
| 2 | 15 | 1,800 | 8 | 1,800 |
| 3 | 15 | 3,000 | 12 | 3,000 |

**Table 2. Result Comparison for the Economic Dispatch (in $)**

| Method | LGM [2] | PSO [2] | γ-PSO [2] | CSA | ECSA |
|---|---|---|---|---|---|
| System 1 | 96,024.42 | 96,024.61 | 96,024.40 | 96024.3719 | 96024.3719 |
| System 2 | 848.241 | 848.204 | 847.908 | 848.3464 | 848.3463 |
| System 3 | 53,053.79 | 53,053.79 | 53,053.79 | 53051.4765 | 53051.4764 |

**Table 3. Result Comparison for the Emission Dispatch**

| Method | | Emission (kg) | | | |
|---|---|---|---|---|---|
| | | $NO_x$ | $SO_2$ | $CO_2$ | Total |
| System 1 | LGM [2] | 14,376.318 | 44,202.359 | 242,406.083 | 300,984.760 |
| | PSO [2] | 14,376.405 | 44,202.506 | 242,407.419 | 300,986.330 |
| | γ–PSO [2] | 14,376.319 | 44,202.360 | 242,406.083 | 300,984.762 |
| | CSA | 14271.7486 | 44302.066 | 241293.1475 | 299,866.962 |
| | ECSA | 14271.5872 | 44302.827 | 241292.5019 | 299,866.916 |
| System 2 | LGM [2] | 571.991 | 4,993.746 | 2,922.820 | 8,488.557 |
| | PSO [2] | 571.729 | 4,995.190 | 2,922.14 | 8,489.059 |
| | γ–PSO[2] | 571.992 | 4,993.747 | 2,922.820 | 8,488.559 |
| | CSA | 571.7745 | 4994.9086 | 2922.2014 | 8488.8845 |
| | ECSA | 572.0224 | 4993.5766 | 2922.9032 | 8488.5021 |

 

| | | | | | |
|---|---|---|---|---|---|
| System 3 | LGM [2] | 21,739.271 | 74,131.817 | 373,122.569 | 468,993.657 |
| | PSO [2] | 21,739.270 | 74,131.817 | 373,122.568 | 468,993.655 |
| | γ–PSO[2] | 21,739.185 | 74,131.681 | 373,121.273 | 468,992.139 |
| | CSA | 21,370.479 | 73,924.733 | 368,209.983 | 463,505.20 |
| | ECSA | 21,247.614 | 73,963.781 | 366,764.279 | 461,975.6 |

**Table 4. Result Comparison for the Compromise Case**

| Method | Total cost ($) | | | $NO_x+SO_2+CO_2$ (kg) | | |
|---|---|---|---|---|---|---|
| | System 1 | System 2 | System 3 | System 1 | System 2 | System 3 |
| LGM[2] | 96421.7250 | 851.0790 | 54337.0270 | 301016.5410 | 8487.8720 | 469025.331 |
| PSO [2] | 96421.7250 | 851.0790 | 54337.0270 | 301016.5410 | 8487.8720 | 469025.331 |
| γ–PSO[2] | 96421.4600 | 852.3880 | 54336.8880 | 301015.1450 | 8489.4380 | 469023.262 |
| CSA | 96420.7711 | 850.0884 | 54333.5640 | 300436.1908 | 8490.8713 | 465612.940 |
| ECSA | 96420.1955 | 850.0896 | 54305.4741 | 300437.8326 | 8490.7346 | 463428.630 |

**Table 5. Comparison of Total Computational Time (in seconds) for Total Three Dispatch Cases**

| Method | LGM [2] | PSO [2] | γ-PSO [2] | CSA | ECSA |
|---|---|---|---|---|---|
| System 1 | 14.83 | 95.36 | 43.44 | 46.5 | 53.4 |
| System 2 | 11.46 | 83.73 | 39.27 | 63.4 | 61 |
| System 3 | 12.26 | 105 | 49.01 | 138.3 | 146 |

## 5. Conclusions

In this paper, the ECSA method has been successfully implemented for solving the MO-GCO-HTS problem with nonconvex objective function. In the ECSA method, the local search ability is enhanced by performing the first modification on the abandoned group since the updated step size is decreased as the current iteration is increased. Moreover, the ECSA can search a better solution in the top group by exchanging information between each two eggs. In addition, the ratio of the number of nests in the top group to that in the abandoned group is also a main factor to decrease the execution time. The effectiveness and robustness of the ECSA are verified on three systems with quadratic fuel cost function and four objectives including three emission objectives and one fuel cost objective. The result comparisons with other methods including the conventional CSA and others in the literature have indicated that the proposed method is better than the compared methods in terms of the total cost, emission and computational time. Therefore, the proposed ECSA method can be a very efficient one for solving the MO-GCO-HTS problems.

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