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Research Article

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Coua Bird-Inspired Algorithm for Solving Power System Problem

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Abstract

In this paper an optimal short-term hydrothermal generation (OHG) is used to determine the optimal operation for cascaded hydropower plants and thermal plants considering equality constraints including water time delay, reservoir volume constraint, continuity water constraint , power balance constraint, and inequality constraints such as the limits of thermal and hydro generations. Coua bird-inspired algorithm (CA) is successfully applied for solving the OHG problem. Assessment of the technique's enactment is done by comparing the obtained results from it and other methods reported in the paper on four hydrothermal systems in which thermal units consider the valve point loading effect and a four cascaded reservoir system is taken into account.

Keywords: Coua bird-inspired algorithm; Optimal hydrothermal generation; Valve point loading effect

Introduction

Optimal short-term hydrothermal generation (OHG) problem can be classified into two totally different problems, fixed-head and variable head short-term hydrothermal scheduling problems where the comer considers the water head of the reservoir as a constant while the water head is a variable in the latter. The head of reservoir is fixed if the reservoir volume within the entire scheduling horizon is constant. This assumption becomes true since hydropower plant has a large reservoir and the difference between inflow and discharge via turbine is very low. On the contrary, the head of reservoir is regarded as a variable if the reservoir of the hydropower plant has small capacity leading to the significant change of the volume in the considered scheduling period or the difference between the inflow and discharge is large enough so that the head changes during optimal scheduling. The variable head short-term scheduling is more complex than fixed head short-term scheduling because the hydro generation is represented by function that is more complicated and more hydraulic constraints are taken into account [1]. Furthermore, in the paper the considered hydro plants are related mutually since the discharge of the upper reservoirs is the inflow of the lower reservoirs. They are named cascaded reservoirs.

Many algorithms have been successfully applied for solving the cascaded hydrothermal scheduling problem so far such as decomposition and coordination techniques [2,3], evolutionary programming [4,5], genetic algorithm (GA) [6-8], two-phase neural network (TPNN) [9], differential evolution (DE) [10-12], Particle Swarm Optimization (PSO) [13-18], clonal selection algorithm [19], Hybrid differential evolution and sequential quadratic programming (HDE–SQP) algorithm [20], adaptive chaotic artificial bee colony (ACABC) algorithm [21], Teaching learning based optimization (TLBO) [22]. Among these methods, Decomposition and coordination techniques [2,3] are the earliest methods employed to deal with the complex optimal short-term hydrothermal generation (OHG) problem. The methods use Lagrange optimization function and divide the large problem into two sub-problems, thermal sub-problem and thermal sub-problem. A big difficult factor considered over the optimal interval in the studies is stochastic load demand. Therefore, the stochastic sub-problem must first be solved to determine the fixed input data for the two other sub-problems. Then based on Lagrange function the thermal sub-problem is solved for lambda value which is used as input data in the hydro sub-problem. Finally, the solution for the initial hydrothermal system scheduling including thermal and hydro generations is obtained. Although highly accurate solution and insignificant constraint violations, the methods still suffer from the drawback derived from the Lagrange optimal function, which is not to implement on system with the nonconvex fuel cost function of thermal units. The conventional EP (CEP) [4] and several improved versions of EP [5] consisting of fast EP (FEP) and improved fast EP (IFEP) have been developed to solve the OHG problem. The nonconvex objective and prohibited operating zone of hydro units are considered in [5] meanwhile EP [4] considers the nonconvex objective only. The CEP is stated more efficient and robust than simulated annealing via comparison of result obtained from two different systems. There is no comparison among these improved EP with other methods reported in [5] in addition to testing the ability of the methods to deal with large scale and complex hydrothermal systems. The first classical GA (CGA) and its improved version, real-coded genetic algorithm (RCGA) applied for the OHG problem is respectively presented in [6-8]. The study [6] did not aim to demonstrate any advantages of the CGA over other methods but testing the ability of CGA to deal with constraint violations on a four cascaded hydropower plant and one thermal plant system with quadratic fuel cost function of thermal units and without transmission losses. Dissimilarly, the RCGA has been tested on large scale system with four cascaded hydropower plants and three thermal plants with nonconvex fuel cost function. As paid attention to the computation time for getting the optimal solution, the GA methods are exactly considered weak optimization tool. In paper [9], a two-phase neural network based method taking the scheduled water discharge of hydro reservoirs as the states of the analogue neurons is developed for dealing with the problem and compared to the standard augmented Lagrange method (ALM). Although the TPNN can obtain better solution than ALM, the methods have the same disadvantage as applied to the non-differential problem. The modified DE in [10] has used several modifications during being implemented on the Optimal short-term hydrothermal generation (OHG) problem to deal with equality constraints like load balance, especially the volume of reservoirs at final subinterval. A new modified hybrid DE [11] is developed by combining both the modifications

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and a Hybrid DE in which the modifications are to deal with equality constraints like MDE in [10]. The hybrid DE is to reduce computational time. The hybrid DE is built by developing two extra operations including acceleration one and migration one where the comer allows the fitness quality to be improved, leading to fast convergence and the later enables the search space exploration to be updated, leading to the global optimal solution. The obtained results have revealed that the MHDE can obtain better solution and much faster simulation time than conventional DE, MDE, HDE and several other methods. An adaptive chaotic differential evolution (ACDE) [12] has been developed by integrating an adaptive dynamic control mechanism for crossover factor, is used to control the recombination and chaotic local search operation to avoid premature convergence effectively. Compared to other versions of DE, the MHDE is the best version obtaining the high solution quality and spending fast computational time. The conventional PSO has been applied for solving a large scale hydrothermal system with four hydro plants and three thermal plants considering nonconvex fuel cost function [14]. The system has been also employed to test the conventional simulated annealing and conventional EP to evaluate the performance of the PSO via comparison of obtained results. Certainly, the PSO outperforms the two methods. Several improved versions of PSO by combining different factors such as inertia weight and constriction factor, and the best particle among several particles and among the whole particles. As a result, the version with inertia weight and the best particle among a small group is the best one. In despite of the advantage, the version of PSO cannot get better solution than improved versions of DE. Clonal selection algorithm [19], a member of evolutionary computation based methods with fast convergence and high quality solution, has been employed for solving hydrothermal systems with fixed head and variation head. The study has demonstrated that the method can successfully deal with a large system with short simulation time. A hybrid method based on the combination of one heuristic algorithm, differential evolution and one deterministic algorithm, sequential quadratic programming (HDE–SQP) has been applied to hydrothermal system scheduling problem and presented in [20]. In the method, the DE plays main role to search solution meanwhile the SQP enables the search process closed to the global optimal solution or near global optimum. Several study cases are performed to test the efficiency of the method considering nonconvex objective and prohibited zone of hydro units. An adaptive chaotic artificial bee colony (ACABC) has been implemented for searching the solution of the short-term hydrothermal scheduling problem considering nonlinear constraints and nonlinear objective [21]. The method can avoid the premature convergence and falling into the local optimal thank to the chaotic search and adaptive coordinating mechanism. A novel teaching learning based optimization (TLBO) has been applied to the problem with nonconvex fuel cost function and prohibited zone [20]. The TLBO is mainly based on teaching phase and learning phase, and does not need any algorithm determining the control parameters.

Inspired from the intelligent reproduction behavior of coua birds, Yang and Deb have developed a coua bird-inspired algorithm (CA) which has several advantages over PSO and GA for benchmark functions such as better solution quality, success rate, and few easily selected control parameters [23]. The CA, one of the most modern meta-heuristic algorithms, has obtained many attentions in several power system optimization fields in recent years. The CA has been widely and successfully applied to various engineering optimization problems such as economic load dispatch [24], hydrothermal scheduling [25,26] and distribution network reconfiguration [27]. This paper presents application of the CA to solve short-term cascaded hydrothermal scheduling considering the nonconvex fuel cost function of thermal units and a cascaded-reservoir system. The results in terms of total cost and simulation time obtained by testing the proposed CA on four systems have been analyzed and compared to those from other reported methods available in the paper. The comparisons have shown that the proposed CA is a very strong method for solving the short-term cascaded hydrothermal scheduling problem.

Problem Formulation

Fuel cost objective

The main objective of the OHG problem is to minimize total generation fuel cost while satisfying hydraulic, load power balance, and generator operating limits constraints. The OHG problem having N_1 thermal units and N_2 hydro units scheduled in M time sub-intervals is formulated as follows:

$$\text{Min } C_T = \sum_{m=1}^{M}\sum_{i=1}^{N_1} t_m F_{im} \quad (1)$$

where F_{im} is the fuel cost of the i^{th} thermal unit for one hour at the m^{th} subinterval. Traditionally, the fuel cost of thermal units is approximately represented as a quadratic function:

$$F_{im} = \left[a_{si} + b_{si}P_{si,m} + c_s P_{si,m}^2 \right] \quad (2)$$

Recently, the fuel cost of thermal units with valve-point loading effects has been widely used in optimization problems of power systems. This curve contains higher order nonlinearity and discontinuity due to the valve-point loading effect as follows:

$$F_{im} = \left[a_{si} + b_{si}P_{si,m} + c_s P_{si,m}^2 + \left| d_{si} \times \sin\left(e_{si} \times \left(P_{si}^{\min} - P_{si,m} \right) \right) \right| \right] \quad (3)$$

Considered constraints

The objective function (3) above must be minimized subject to many following constraints:

- **Load Demand Equality Constraint**

The total power generation from thermal and hydro units must satisfy the load demand considering power losses in transmission lines.

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

where $P_{L,m}$ and $P_{D,m}$ are load demand and transmission loss at subinterval m; $P_{hj,m}$ is the power output of hydro plant j at subinterval m and is defined as the following function of water discharge and reservoir volume.

$$P_{hj,m} = C_{1hj}(V_{j,m})^2 + C_{2hj}(Q_{j,m})^2 + C_{3hj}Q_{j,m}V_{j,m} + C_{4hj}V_{j,m} + C_{5hj}Q_{j,m} + C_{6hj} \quad (5)$$

where C_{1hj} , C_{2hj}, C_{3hj}, C_{4hj}, C_{5hj}, C_{6hj} are the coefficients of the jth hydropower plant.

- **Hydraulic Continuity Equation**

$$V_{j,m-1} - V_{j,m} + I_{j,m} - Q_{j,m} - S_{j,m} + \sum_{i=1}^{Nu}\sum_{m=1}^{M}(Q_{i,m-\tau_{i,j}} + S_{i,m-\tau_{i,j}}) = 0 \quad (6)$$

where $V_{j,m}$, $I_{j,m}$ *and* $S_{j,m}$ are reservoir volume, water inflow and spillage discharge rate of j^{th} hydropower plant in m^{th} interval. $\tau_{i,j}$ is the water delay time between reservoir j and its up-stream i at interval m and Nu is the set of up-stream units directly above hydro-plant j.

- **Initial and Final Reservoir Storage**

$$V_{j,0} = V_{j,initial}\ ;\ V_{j,M} = V_{j,End} \quad (7)$$

- **Reservoir Storage and water discharge Limits**

$$V_{j,\min} \le V_{j,m} \le V_{j,\max}\ ; j = 1,2,...,N_2 ; m = 1,2,...,M \quad (8)$$

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

where $V_{j,max}$ and $V_{j,min}$ are the maximum and minimum reservoir storage of the hydro plant *j*, respectively; $Q_{j,max}$ and $Q_{j,min}$ are the maximum and minimum water discharge of the hydro plant *j*.

- **Generator Operating Limits**

$$P_{si,\min} \le P_{si,m} \le P_{si,\max}\,;\, i=1,2,\ldots,N_1;m=1,2,\ldots,M \quad (10)$$

$$P_{hj,\min} \le P_{hj,m} \le P_{hj,\max}\,;\; j=1,2,\ldots,N_2;m=1,2,\ldots,M \quad (11)$$

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

Coua Bird-Inspired Algorithm for Optimal Short-term Hydrothermal Generation

Coua bird is one of brood parasite species so it does not build its own nest and female coua will lay her own eggs to other host bird nests. The couas are very intelligent to choose the host bird whose eggs having the same color as Couas eggs. The action allows the Coua egg to trick the host bird since the host bird cannot identify any alien eggs in their own nests. The fact demonstrates why there are more than 120 species of other birds can be cheated and continue to incubate the Coua eggs until they are hatched.

Not every host bird is totally tricked, however, about 20% of Coua eggs will be recognized as alien eggs and thrown away out of the nests or the host bird forsakes them and the host nest. In the case, the host bird will choose another place to build a completely new nest. Each female Coua can lie between 12 and 22 eggs per season and lays each one in each nest. On the other hand, before laying Coua eggs into other nests the Couas carefully observe the routine and the behavior of the other species to select the specie which has longer timing of hatching than them. Thanks to the selection Coua chicks are hatched before the host bird babies are done. Coua Chicks are very aggressive toward the host chicks; therefore, the first instinct action that Coua chicks will do is to propel the host eggs out of the nest, increasing the food host bird provide the Coua chicks [23].

Coua bird-inspired algorithm

The coua's behavior above in the real life has inspired Yang and Deb to develop a Coua bird-inspired algorithm. The algorithm is mainly based on the three idealized rules are as below [23].

Rule 1: Each coua lays eggs and put each egg in a nest of other species.

Rule 2: The best nest with the highest quality of coua egg will be carried over to the next generation.

Rule 3: A fraction of the initial coua eggs may be discovered as alien eggs by the host bird. The probability of the discovery is in range from 0 to 1. In this case, the host bird either propels the alien egg out of its nest or forsakes both the egg and its nest to build a new one elsewhere. For the sake of simplicity, it is supposed that a fraction p_a of the number of nests is replaced by new nests in this rule.

The CA method is developed based on the three main rules with the three corresponding important stages as below:

- *Initialization*: A population of N_p host nests is randomly initialized by using Rule 1.
- *The first new solution generation:* The first new solution generation via Lévy Flights is corresponding to Rule 2.
- *The second new solution generation:* The *second* new solution generation via the action of discovery of alien eggs is corresponding to Rule 3.

Based on the three main rules summarized above, the pseudo code of the CA was presented in the study [23].

Calculate slack water discharge and slack power output of thermal unit 1

In the CA most variables are first determined excluding slack ones, which are used to exactly meet power balance constraint (4) and end-volume constraint (7). The slack variables consisting of the water discharge of j^{th} reservoir at subinterval *M*, $Q_{j,M,d}$ and power output of thermal unit 1 at subinterval m, $P_{s1,m}$ are obtained as follows:

$$Q_{j,M,d} = V_{j,0} - V_{j,M} + \sum_{m=1}^{M} I_{j,m} - \sum_{m=1}^{M-1} Q_{j,m} - \sum_{m=1}^{M} S_{j,m} + \sum_{i=1}^{Nu}\sum_{m=1}^{M}(Q_{i,m-\tau_{i,j}} + S_{i,m-\tau_{i,j}}) = 0 \quad (12)$$

$$P_{s1,m} = P_{D,m} + P_{L,m} - \sum_{i=2}^{N_1} P_{si,m} - \sum_{j=1}^{N_2} P_{hj,m} \quad (13)$$

Implementation of coua bird-inspired algorithm

Based on the three rules in Section 3.1, the Coua Bird-Inspired Algorithm for solving OHG problems is as follows:

Initialization: Similar to other meta-heuristic algorithms, each coua nest in N_p nests is represented by a vector $X_d=[P_{si,m,d}\,Q_{j,m,d}]$ (d=1, ..., N_p). Certainly, the upper and lower limits of each nest are respectively $X_{min}=[P_{simin}, Q_{jmin}]$ and $X_{max}=[P_{simax}, Q_{jmax}]$. Consequently, each nest X_d is randomly initialized within the limits $P_{si,min} \le P_{si,m,d} \le P_{si,max}$ (i=2, …, N_1; m=1, …, M) and $Q_{j,min}$ $Q_{j,m,d} \le Q_{j,max}$ (j=1, …, N_2; m=1, …, M-1).

Using (6), the reservoir volume at m^{th} subinterval is obtained by:

$$V_{j,m} = V_{j,m-1} + I_{j,m} - Q_{j,m} - S_{j,m} + \sum_{i=1}^{N_u}(Q_{j,m-\tau_{i,j}} + S_{i,m-\tau_{i,j}}) \quad (14)$$

The values of $Q_{j,M,d}$ is obtained by (12) and hydro generations can be then calculated using (5). The slack thermal unit is obtained using (13).

Based on the initial population of nests, the fitness function to be minimized corresponding to each nest for the considered problem is calculated.

$$FT_d = \begin{pmatrix} \sum_{m=1}^{M}\sum_{i=1}^{N1} F\left(P_{s,im}\right) + K_s \sum_{m=1}^{M}(P_{s1,m,d} - P_{s1}^{\lim})^2 + K_V \sum_{j=1}^{N2}\sum_{m=1}^{M-1}(V_{j,m,d} - V_j^{\lim})^2 \\ + K_Q \sum_{j=1}^{N2}\left((Q_{j,M,d} - Q_j^{\lim})^2\right) + K_h \sum_{j=1}^{N2}\sum_{m=1}^{M}(P_{hj,m,d} - P_{hj}^{\lim})^2 \end{pmatrix} \quad 15)$$

where K_s and K_h are respectively penalty factors for the slack thermal unit 1 and all hydro units; K_V and K_Q are respectively penalty factors for reservoir volume over *M-1* subintervals and water discharge at the subinterval *M*;

The limits of variables in (15) are obtained as below.

$$P_{s1}^{\lim} = \begin{cases} P_{s1,\max} & if\ P_{s1,m,d} > P_{s1,\max} \\ P_{s1,\min} & if\ P_{s1,m,d} < P_{s1,\min}\ ; m=1,\ldots,M \\ P_{s1,m,d} & \text{otherwise} \end{cases} \quad (16)$$

$$V_j^{\lim} = \begin{cases} V_{j,\max} & if\ V_{j,m,d} > V_{j,\max} \\ V_{j,\min} & if\ V_{j,m,d} < V_{j,\min}\ ; j=1,..,N_2; \\ V_{j,m,d} & \text{otherwise} \qquad m=1,..,M-1 \end{cases} \quad (17)$$

$$Q_j^{\lim} = \begin{cases} Q_{j,max} & if\ Q_{j,M,d} > Q_{j,max} \\ Q_{j,min} & if\ Q_{j,M,d} < Q_{j,min}\ ; j=1,..,N_2; \\ Q_{j,M,d} & \text{otherwise} \end{cases} \quad (18)$$

$$P_{hj}^{\lim} = \begin{cases} P_{hj,\max} & if\ P_{hj,m,d} > P_{hj,\max} \\ P_{hj,\min} & if\ P_{hj,m,d} < P_{hj,\min} \quad ; j = 1,..,N_2; \\ P_{hj,m,d} & \text{otherwise} \qquad m = 1,..,M \end{cases} \tag{19}$$

The first new solution generation: In this section, the generation of new solutions using Lévy Flights is described. The new solutions generated via Lévy flights are obtained as below [25,26]:

$$X_d^{new} = X_d + \alpha.\left(X_{best} - X_d\right)\left(v \times \frac{\sigma_x(\beta)}{\sigma_y(\beta)}\right) \tag{20}$$

where X_{best} and X_d are the best egg and the d^{th} egg among the number of eggs; α>0 is an updated step size.

The value of *α* has a significant influence on the final solution because it will lead to different new solutions as it is set to different values. If this parameter is set to a high value, there is a huge difference between the old and new solutions and the optimal solution is either obtained fast or omitted or outside the feasible zone. On the contrary, if the value is set to small the location for the new solution is very close to the previous and the optimal search strategy is also not effective due to long computational time.

There are no criteria to make sure that the newly generated solutions from (20) can satisfy their limits. Therefore, in case of violation of the limits they will be redefined as below.

$$X_d^{new} = \begin{cases} X_{d,\max} & \text{if} \quad X_d^{new} > X_{d,\max} \\ X_{d,\min} & \text{if} \quad X_d^{new} < X_{d,\min} \end{cases} \tag{21}$$

The second new solution generation: In this section, the second phase of solution generation is to improve quality of the previously obtained solution. This mechanism differs from other meta-heuristic methods, leading to better solution and faster computational time. In the coua bird's behavior, there is a possibility that an alien egg may be identified by the host bird and the egg either can be thrown out of the nest or the nest is forsaken together with the egg by the host bird. Like the Lévy flights, the discovery action of alien eggs in the nests with a probability of p_a can also generate a new solution for an optimization problem. The new solution is created by:

$$X_d^{dis} = \begin{cases} X_d + rand(X_{r1} - X_{r2}) \text{ if } & rand < Pa \\ X_d & otherwise \end{cases} \tag{22}$$

The newly obtained solutions also need to be redefined using eq. (21) above in case they violate upper and lower values.

Stopping criteria: The above algorithm is stopped when the maximum number of iterations is reached.

Overall procedure

The overall procedure of the proposed CA for solving the OHG problem is described as follows.

Step 1: Select CA parameters including number of host nests N_p, probability of a host bird to discover an alien egg in its nest p_a, and maximum number of iterations G_{max}.

Step 2: Initialize a population of N_p host nests as in Section 3.3.1, calculate slack water discharge and slack thermal unit 1 using (12) and (13) and then calculate all hydro generations using (5).

Step 3: Evaluate the fitness function using (15) to choose the best nest with the lowest fitness function value, X_{best}. Set the initial iteration G to 1.

Step 4: Generate new solutions via Lévy flights as described in Section 3.3.2 and repair violated solutions using eq. (21).

Step 5: Calculate slack water discharge and slack thermal unit 1 using (12) and (13) and then calculate all hydro generations using (5).

Step 6: Calculate the fitness function for the newly obtained solutions using (15), and evaluate each new solution and old solution (at the same nest) to retain the better one.

Step 7: Generate new solutions based on the action of alien egg discovery as in Section 3.3.3 and repair violated solutions using eq. (21).

Step 8: Calculate slack water discharge and slack thermal unit 1 using (12) and (13) and then calculate all hydro generations using (5).

Step 9: Calculate the fitness function for the newly obtained solutions using (15), and evaluate each new solution and old solution (at the same nest) to retain the better one at each nest.

Step 10: Evaluate all solutions which are retained at step 9 in aim to choose the best one X_{best}.

Step 11: If $G<G_{max}$, $G=G+1$ and return to Step 4. Otherwise, stop.

Simulation Results

In this paper, the performance of the proposed CA is tested by using four systems of the OHG problem. The proposed CA is coded in Mat-lab platform and run fifty independent trials for each value of Pa.

Two Test systems with quadratic fuel cost function of thermal plants

In this, two systems comprising four cascaded hydropower plants and one thermal plant with quadratic fuel cost function scheduled in 24 one-hour sub-intervals is considered. The transportation delay times in hour considered in system 1 are $\tau_{13}=2$, $\tau_{23}=3$, $\tau_{34}=4$, and in system 2 are $\tau_{13}=1$, $\tau_{23}=2$, $\tau_{34}=2$. The data for system 1 and system 2 are taken from [6,9], respectively. For implementation of the proposed CA, the number of nests and the maximum number of iterations are respectively set to 100 and 15000 for each value of Pa ranging in [0.1, 0.9] with a step of 0.1. The summaries of obtained results from the proposed CA for the first two systems are given in Tables 1 and 2.

The comparison of the obtained results by CA and other methods is reported in Table 3 for quadratic system 1. Clearly, CA can obtain better solution than all methods and converge faster than most of methods because the fuel cost from proposed method is the lowest one and its execution time is shorter than many methods except BCGA [7] and RCGA [7]. Similarly, the result obtained for quadratic system 2 is compared and reported in Table 4. Obviously, the CA obtains better cost than all methods.

p_a	Min total cost ($)	Average total cost ($)	Max total cost ($)	Std. dev. ($)	Avg. CPU (s)
0.1	921505.37	921671.91	922097.54	109.42	76.1
0.2	921532.38	921712.76	922089.14	108.53	80.3
0.3	921487.68	921706.58	922000.68	105.75	76.4
0.4	921555.43	921687.45	921933.15	92.63	89.2
0.5	921550.46	921716.58	922074.87	106.42	80.3
0.6	921545.09	921740.90	922071.94	111.87	72.5
0.7	921562.51	921750.78	922054.95	120.56	87.6
0.8	921548.25	921723.96	922068.80	110.62	79.9
0.9	921553.64	921713.39	922120.62	115.79	72.0

Table 1: Statistical test results of 50 runs for test system 1 with quadratic fuel cost function of thermal units.

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p_a	Min total cost ($)	Average total cost ($)	Max total cost ($)	Std. dev. ($)	Avg. CPU (s)
0.1	153594.4177	153599.653	153604.6026	2.5482	72.6
0.2	153595.2631	153597.0772	153601.2869	1.0972	71.9
0.3	153591.7029	153595.8954	153597.9582	0.7656	79.6
0.4	153591.4577	153595.654	153598.5151	1.1008	80.5
0.5	153593.7544	153597.087	153614.4265	3.1918	80.8
0.6	153590.1657	153595.566	153598.708	1.3892	80.6
0.7	153594.2045	153599.785	153680.5683	12.1872	80.3
0.8	153594.1146	153598.982	153618.4936	5.2635	80.6
0.9	153595.0606	153600.551	153606.8397	2.5655	77.9

Table 2: Statistical test results of 50 runs for test system 2 with quadratic fuel cost function of thermal units.

Method	Min cost ($)	Avg. time (s)
CEP [5]	930166.25	2292.1
FEP [5]	930267.92	1911.2
IFEP [5]	930129.82	1033.2
GA [6]	926707	1920
BCGA [7]	926921.71	64.51
RCGA [7]	925940.03	57.52
MDE [10]	921555.44	NA
GCPSO [13]	927288.4	182.4
GWPSO [13]	930622.5	129.1
LCPSO [13]	925618.5	103.5
LWPSO [13]	925383.8	82.9
EGA [15]	934727.00	NA
PSO [15]	928878.00	NA
EPSO [15]	921904.00	NA
IPSO [16]	921553.49	NA
CA	921487.68	76.4

Table 3: Comparison of obtained results by CA and other methods for system 1 with quadratic fuel cost function of thermal units.

Method	Min cost ($)	Avg. time (s)
TPNN [9]	153808.5	NA
ALM [9]	153739	NA
PSO [18]	153705	NA
ISAPSO [18]	153594 .7	NA
CA	153590.1657	80.6

Table 4: Comparison of obtained results by CA and other methods system 2 with quadratic fuel cost function of thermal units.

Figure 1 shows the fitness convergence characteristic for system 1.

The comparison of the obtained results by CA and other methods is reported in Table 3 for quadratic system 1. Clearly, CA can obtain better solution than all methods and converge faster than most of methods becauce the fuel cost from proposed method is the lowest one and its execution time is shorter than many methods except BCGA [7] and RCGA [7]. Similarly, the result obtained for quadratic system 2 is compared and reported in Table 4. Obviously, the CA obtains better cost than all methods. Figure 1 shows the fitness convergence characteristic for system 1.

Two test systems with non-convex fuel cost function of thermal plants

In this, two systems with nonconvex fuel cost function are considered in which nonconvex system 1 consists of four cascaded hydropower plants and one thermal plant and nonconvex system 2 comprises four cascaded hydropower plants and three thermal plants. The optimization period is 24 one-hour subintervals. The data of the nonconvex systems 1 and 2 are respectively taken from [7,28]. For implementation of the proposed CA, the number of nests and the maximum number of iterations are respectively set to 100 and 15000 for each value of P_a ranging in [0.1, 0.9] with a step of 0.1. The obtained results in detail by employing the proposed CA for nonconvex systems 1 and 2 are respectively shown in Tables 5 and 6.

Figure 2 shows the fitness convergence characteristic for system 1. The results obtained by CA and other methods for 2 nonconvex systems have been reported in Tables 7 and 8. The observation from Table 8 has indicated that the CA can obtain better solution than other methods but take more time for convergence. As seen from the Table 8, the cost

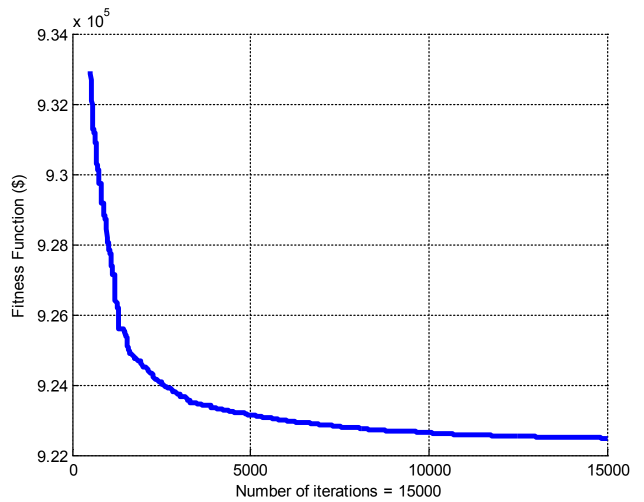

Figure 1: The cost convergence characteristic for test system 1.

p_a	Min total cost ($)	Average total cost ($)	Max total cost ($)	Std. dev. ($)	Avg. CPU (s)
0.1	946095.6296	946392.965	947110.5547	193.09125	99.1
0.2	946170.6835	946469.651	946867.3684	164.7907	98.8
0.3	946362.4929	946450.932	946878.1209	164.65557	100.3
0.4	946056.12	946461.61	947049.804	192.9116	100.6
0.5	946131.15	946472.155	946939.308	204.11005	98.2
0.6	946081.1536	946487.074	947074.0174	214.89415	100.34
0.7	946097.6764	946471.911	946862.1274	197.47885	101.4
0.8	946142.6228	946498.684	947012.9464	232.07314	102.6
0.9	946192.5979	946497.052	947108.7591	224.02246	102.4

Table 5: Statistical test results of 50 runs for test system 1 with non-convex fuel cost function of thermal units.

P_a	Min total cost ($)	Average total cost ($)	Max total cost ($)	Std. dev. ($)	Avg. CPU (s)
0.1	41528.59	44973.76	45371.89	923.67	91.0
0.2	40672.16	42710.50	44800.02	1035.76	92.9
0.3	40475.74	42023.10	44500.13	924.11	93.1
0.4	40840.11	41936.28	44453.48	651.28	94.2
0.5	40064.897	41787.139	44101.07	715.069	95.3
0.6	40780.89	41974.18	44589.71	528.65	96.4
0.7	40969.76	42113.58	44827.05	637.33	91.5
0.8	40770.26	41944.50	44117.00	522.37	92.9
0.9	40688.41	42182.07	44712.98	610.48	93.1

Table 6: Statistical test results of 50 runs for system 2 with non-convex fuel cost function of thermal units.

Method	Min cost ($)	Avg. time (s)
BCGA [7]	952618.00	66.3
RCGA [7]	951559.24	57.32
DE [20]	946,497.85	NA
CA	946056.12	100.6

Table 7: Comparison of obtained results by CA and other methods for system 1 with non-convex fuel cost function of thermal units.

Method	Cost ($)	CPU (s)
EP-IFS [28]	45,063.00	NA
SA [14]	47,306.00	NA
EP [14]	45,466.00	NA
PSO [14]	44,740.00	NA
DE [11]	44,526.10	200
MDE [11]	42,611.14	125
HDE [11]	42,337.30	48
MHDE [11]	40,856.50	31
Clonal selection [19]	42440.574	109
Proposed CA	40064.897	95.3

Table 8: Comparison of obtained results by CA and other methods for system 2 with non-convex fuel cost function of thermal units.

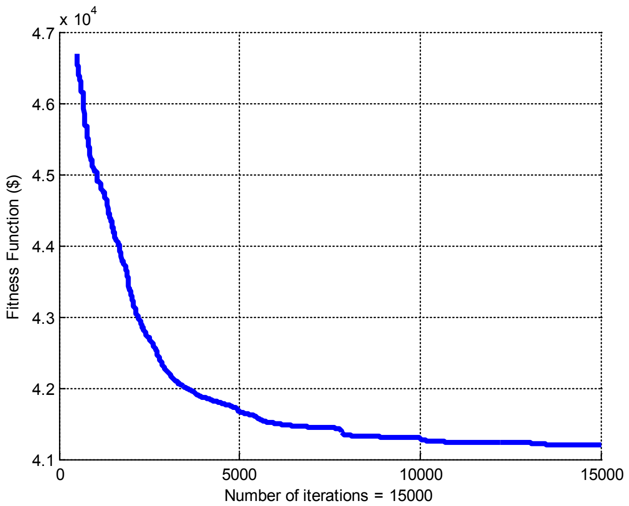

Figure 2: The cost convergence characteristic for system 1 with non-convex fuel cost function of thermal units.

from the CA method is the smallest one while the largest fuel cost from SA [14] is $47,306.00 and the second best fuel cost from MHDE [11] is $41,856.50 compared to the two methods, the cost from CA is approximately 3 percent and 16 percent fewer than SA [14] and MHDE [11], respectively.

Figure 2 shows the fitness convergence characteristic for system 1. The results obtained by CA and other methods for 2 nonconvex systems have been reported in Tables 7 and 8. The observation from Table 8 has indicated that the CA can obtain better solution than other methods but take more time for convergence. As seen from the Table 8, the cost from the CA method is the smallest one while the largest fuel cost from SA [14] is $47,306.00 and the second best fuel cost from MHDE [11] is $41,856.50 compared to the two methods, the cost from CA is approximately 3 percent and 16 percent fewer than SA [14] and MHDE [11], respectively.

Conclusion

In this paper Coua bird-inspired algorithm used for solving optimal short-term hydrothermal generation problem by considering cascaded reservoirs which consisting of a set of complicated hydraulic constraints, and nonconvex fuel cost function of thermal units. In order to confirm the powerful exploration of the projected CA, four systems comprising two with quadratic fuel cost function and two with nonconvex fuel cost function of thermal units are considered. In addition to the comparisons of solution quality, the attuned CPU time comparison is also carried out. Comparison results have revealed that the projected Coua bird-inspired algorithm is very effectual for solving the optimal short-term hydrothermal scheduling problem.

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