

A Novel Effective Meta-Heuristic Algorithm for BI-Objective Dispatch of Power Systems

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Abstract: This paper proposes an Adaptive Selective Cuckoo Search Algorithm (ASCSA) for solving bi-objective short-term hydrothermal scheduling (BOSTHTS). The major purpose of the BOSTHTS problem is to reduce electric generation fuel cost and polluted emission from all considered thermal generating units over a scheduled intervals. In addition, the problem also takes all constraints of hydrothermal power systems such as real power demand of load, limitations of generations and limitations of reservoirs into account. The proposed method is constructed by tackling all drawbacks of classical Cuckoo Search algorithm (CCSA) so as to shorten number of iterations and fast converge to good solutions. The proposed method together with CCSA and another modified version of CCSA (MCSA) are implemented for two different systems with different types of fuel cost form and emission form and results from these methods are also compared to other existing methods. Objective comparisons and computation time comparisons indicate that the proposed method is superior to CCSA, MCSA and other compared methods. As a result, the proposed method is considered to be a strong optimization method for the considered BOSTHTS problem.

Keywords: Adaptive selective random walk, new selection technique, multiobjective, hydrothermal power system, fitness function.

1. Introduction

The short term hydrothermal scheduling (STHTS) is a complex problem with the task of determining generated power of considered thermal and hydro units, and with the purpose of reducing total electric generation fossil fuel cost of all thermal units as much as possible over a scheduled time while equality constraints and inequality constraints regarding reservoirs of hydropower plants and all generators must be exactly satisfied [1]. However, the objective of minimizing the total fossil fuel for electricity generations is not a single target since thermal units are the main source of producing polluted emissions consisting of CO_2 , SO_2 and NO_x [2]. Consequently, the objective of ST HTS problem can be extended to consider the reduction of both total fuel cost and the gaseous emission as a result [2-5].

Many studies have proposed different original algorithms and improved version of these original algorithms for solving the BOSTHTS problem in aim to reduce the fuel cost and emission. These previous studies have tended to classify the complex level of the problem based on the form of the electric generation fossil fuel and the emission functions. The electric generation cost function can be expressed as the second order function or a nonconvex function if effects of valve during the operation process of thermal units are neglected or considered. Besides, the emission can be represented as a second order equation or the sum of the second order equation and another exponential function. The use of both the nonconvex fuel cost function and the sum equation is a big challenge for applied methods in addition to the large scale of power systems. Simulated annealing algorithm (SAA) [3] has been applied to only one system of the BOSTHTS problem where the most complex of using both nonconvex electric

generation cost function and exponential emission function. This study has searched some solutions corresponding some values of weight factors corresponding to fuel cost and emission and then the goal-attainment method has been employed to determine the best solution with suitable cost and suitable amount of emission. Therefore, the lowest emission and the lowest emission could not be reasonable compared to other reports from other studies. γ -PSO method [4], a combination of Particle swarm optimization and Lagrange function (γ -PSO), has been proposed for solving three larger systems considering both fuel cost and emission. Similar to LGM in [2], γ -PSO method has constructed a Lagrange function and then coordination equations has been used to obtain the optimal solution. Contrary to other meta-heuristic algorithms, γ -PSO method has considered γ Lagrange multiplier as a control variable in the position of each particle and then lambda Lagrange multiplier has been obtained. As a result, optimal generations of thermal units and hydro units have been determined by substituting these Lagrange multiplier into these coordination functions. The selection of control variable could allow γ -PSO method converge to optimal solutions very fast; however, the limitation of using Lagrange function have prevented γ -PSO from solving systems where valve point loading effects of thermal unit were considered. An improved genetic algorithm based on sorting non-dominated solutions (NS-GA) [5] has been suggested for dealing with two systems with nonconvex fuel cost function and the sum function of emission. This method has been considered better than other method such as Real-coded genetic algorithm (RC-GA) and multi-objective differential evolution (MO-DE) since its cost and emission were less than those of RC-GA and MO-DE. In spite of the advantage, this method has also suffered from long execution time for obtaining optimal solution due to the characteristic of conventional GA. The combination of an enhanced genetic algorithm, updated multiplier and the penalty method forming EGA-UM method has been proposed and presented in [6] for solving the complex problem. This method was superior to conventional GA and GA-UM based on the comparison of fuel cost and emission. The combination of predatorprey algorithm and Powell search algorithm (PPA-PSA) [7] has been developed for solving the BOSTHTS problem. PPA-PSA has been considered a potential method by owning both strong global search performed by PPA and powerful local search performed by PS. PPA-PSA had some advantages of CPSO such a low number of control parameters and simple implementation but it had to cope with some limits such as easily falling into local optimal solutions and lack of effective capability to deal with the constraints. In addition, a penalty method for tackling the equality constraints and inequality constraints has also been used with PPA-PSA to construct a stronger method, called PPA-PSA-PM. Result comparisons have indicated that PPA-PSA-PM was the best method among several implemented methods such as CPSO, CPSO with Penalty method (CPSO-PM), PPA, PPA with penalty method (PPA-PM) and PPA-PSA. However, the best method has run the search process long for both small size systems and large size systems. The combination of improved model and multi-objective distribution algorithm (IM-MODA) [8] has solved the HTS problem with nonconvex fuel cost function of thermal units successfully. However, there was no any demonstration that the improvement in the method was efficient because there was no comparison between the method and other ones. Furthermore, the fuel cost and emission comparisons have pointed out that IM-MODA was worse than MO-DE, NS-GA and EGA-UM since it had higher cost and higher emission.

Conventional cuckoo search algorithm (CCSA), a recently new meta-heuristic algorithm, created by Yang et al in 2009 [9] by inspiring intelligent behavior of cuckoo birds. Wide and successful applications of the CCSA for different optimization problems in different fields have been studied such as wireless sensor networks [10], wind farm layout design problem [11], optimal heat and power generation [12]. In spite of the good efficiency of CCSA, there have been many studies, which have identified the disadvantages of this method and brought up several modifications on the CCSA [13-15]. These studies have tried to improve the performance of CCSA by fulfilling different modifications but they did not point out clear weak points of the method. Consequently, we point out drawbacks of CCSA and then we will analyze the disadvantages and propose improvements. As stated in [16], the search process of CCSA has three stages consisting of global search, local search and selection procedures. The selection

procedure keeps better solution between old solution and new solution at the same nest while global search procedure and global search procedure aim to effective search zone. CCSA has two times producing new solutions at each iteration via Lévy flights and mutation operation in which Lévy flights acts as global search and mutation operation acts as local search. CCSA has better performance than most original methods but its search ability can be further improved because its mutation operation cannot exploit the highest local search ability and its selection can keep less effective solutions. In order to get fast search ability and converge to the best solutions with lower fitness value, improved version of CCSA (ASCSA) is formed in the paper by changing two techniques of CCSA such as mutation operation and selection operation into new selection technique and adaptive mutation technique. The new selection technique becomes more promising than the old one due to the change of strategy keeping solutions. It gathers all old and new solutions into a big group and then leading solution with the best fitness values are retained. The adaptive mutation technique can expand and narrow search space for each considered solution based on quality of the considered solution and the best solution. Namely, larger search zone is suggested in case the considered solution is close to the best solution but smaller search zone is selected for the case of high distance between the considered solution and the best solution. For testing the impact of the two proposed techniques, bi-objective HTS problem with two different systems taking total power loss of branches and valve effects of thermal generating units into account is employed. The first system is comprised of two thermal units and two hydro units without considering valve point loading effects on thermal units and the second one is comprised of two hydro units and four thermal units considering the valve effects. The performance of ASCSA will be evaluated via the comparison with two Cuckoo search variants including CCSA and Modified CSA (MCSA), and other methods reported in the paper such as RC-GA, NS-GA, MO-DE, SPEA, GA-MU, EGA-UM, CPSO-PM, PSO, PPA, PPA-PM, PPA-PSA and PPA-PSA-PM.

2. Formulation of BOSTHTS Problem

A. Objectives of BOSTHTS Problem

The objectives are to reduce both electricity generation cost and polluted emission as below

$$Min F = \psi_1 \sum_{i=1}^{N_1} F_{1i} + \psi_2 \sum_{i=1}^{N_1} F_{2i}$$
(1)

Where Ψ_1 and Ψ_2 are respectively weights of electric generation cost and polluted emission, and constrained by [9]:

$$\psi_1 + \psi_2 = 1 \tag{2}$$

$$0 \le \psi_1, \psi_2 \le 1 \tag{3}$$

And F_{1i} and F_{2i} are the electric generation cost and polluted emission of the *ith* thermal generating unit. The electric generation cost can be approximately represented in terms of formula (4) corresponding to the case of neglecting valve point loading effect or formula (5) corresponding to the case of considering the valve point loading effects [1].

$$F_{1i} = \begin{bmatrix} a_{si} + b_{si}P_{si} + c_{si}P_{si}^2 \end{bmatrix}$$

$$\tag{4}$$

$$F_{1i} = \left[a_{si} + b_{si} P_{si} + c_{si} P_{si}^2 + \left| d_{si} \times \sin\left(e_{si} \times \left(P_{si,\min} - P_{si}\right)\right) \right| \right]$$
(5)

where a_{si} , b_{si} , c_{si} , d_{si} and e_{si} are coefficients of electric generation cost function of the *ith* thermal generating unit; $P_{si,min}$ is the lowest power output of unit *i*.

Besides, polluted emission mass released by the *ith* thermal generating unit can be modeled as the sum of the second order function and exponential function shown in the following expression [7]:

$$F_{2i} = a_{esi} + b_{esi}P_{si} + c_{esi}P_{si}^2 + d_{esi}\exp(e_{esi}P_{si})$$
(6)

where a_{esi} , b_{esi} , c_{esi} , d_{esi} , and e_{esi} are coefficients of emission function.

B. Hydraulic and System constraints

B.1. Balance between demand and supply: In order to keep frequency within working range, demand side and supply side together with power loss must follow the rule below:

$$\sum_{i=1}^{N_1} P_{si,m} + \sum_{j=1}^{N_2} P_{hj,m} - P_{L,m} - P_{D,m} = 0; m = 1, \dots, M$$
(7)

where N_1 and N_2 are the number of thermal generating units and hydro units; M is the number of all subintervals; $P_{D,m}$ is real power required by load in the *mth* subinterval ; and $P_{L,m}$ is the power losses in transmission lines in subinterval and is obtained by[2]:

$$P_{L,m} = \sum_{i=1}^{N_1+N_2} \sum_{j=1}^{N_1+N_2} P_{i,m} B_{ij} P_{j,m} + \sum_{i=1}^{N_1+N_2} B_{0i} P_{i,m} + B_{00}$$
(8)

B.2. Balance between used water volume and available water volume: discharged water volume through turbines and predetermined water volume by operators are constrained by:

$$\sum_{m=1}^{M} t_m q_{j,m} = W_{aj}; j = 1, ..., N_2$$
(9)

Where W_{aj} is the amount of available water for the j^{th} hydropower plant over scheduled horizon; t_m is the duration subinterval m; and $q_{j,m}$ is the discharged water, which is obtained by using the model below[2].

$$q_{j,m} = a_{hj} + b_{hj}P_{hj,m} + c_j P_{hj,m}^2$$
(10)

where a_{hj} , b_{hj} and c_{si} are coefficients of discharged water function via the *ith* hydro turbine.

B.3. Real power generation limitations: each hydro and thermal unit have to produce power within predetermined ranges as shown in the following inequalities

$$P_{si,\min} \le P_{si,m} \le P_{si,\max} \tag{11}$$

$$P_{hi\min} \le P_{hi\max} \le P_{hi\max} \tag{12}$$

where $P_{si,max}$ and and $P_{hj,max}$ are maximum power of the *ith* thermal generating unit and the *jth* hydro unit; and $P_{hj,min}$ is the minimum power of the *jth* hydro unit.

3. Adaptive Selective Cuckoo Search Algorithm

A. Lévy flight random walk

Lévy flight random walk is a mechanism for generating the first new solutions. For each current solution X_d , new solution is produced by using the following expression [9].

$$X_{d,newl} = X_d + \alpha \left(X_d - G_{best} \right) \oplus Levy(\beta)$$
⁽¹³⁾

where $X_{d,newl}$ is a new solution of X_d ; G_{best} is the global best solution in all considered solutions; α is the scaling factor; and Levy(β) is the Lévy distribution.

B. Adaptive selective random walk (ASRW)

The proposed adaptive selective random walk is also a technique to produce the second new solutions. The proposed ASRW is developed by improving selective random walk (SRW) of CCSA. The original ASRW is shown in the following equation.

$$X_{d,new2} = \begin{cases} X_d + rand.(X_{r1} - X_{r2}) & \text{if } R_d < P_a \\ X_d & \text{otherwise} \end{cases}$$
(14)

Where P_a is the probability that a fraction of solutions is newly generated; R_d is a random number for solution d; X_{rl} and X_{r2} are randomly taken solutions from the current population.

In case of using (14), if a current best solution G_{best} is far from the real optimal one and the old solution is very close to *Gbest*, a new solution will be very close to the old solution and the algorithm will be terminated and find local optimum when using only the two point factor. To overcome the hopeless circumstance, a new equation for generating new solutions is proposed

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as below.

$$X_{d,new2} = X_d + rand.(X_{r1} + X_{r2} - X_{r3} - X_{r4})$$
(15)

To determine either using (14) or (15), a new selection condition with the use of FDR is proposed in eq. (16) in which FT_d and FT_{best} are the fitness function of solution X_d and the best solution, respectively. When FDR_d is less than tolerance ε , eq. (16) is used. Otherwise, eq. (15) is employed. The tolerance ε is a predetermined value ranging in [10⁻⁵, 10⁻⁴, 10⁻³, 10⁻², 10⁻¹].

$$FDR_{d} = \frac{FT_{d} - FT_{best}}{FT_{best}}$$
(16)

As a result, the adaptive random walk is illustrated via the following modified equation.

$$X_{d,new2} = \begin{cases} X_{d} + rand.(X_{r1} - X_{r2}) \ if \ (R_{d} < P_{a}) \& (FDR_{d} > \varepsilon) \\ X_{d} + rand.(X_{r1} + X_{r2} - X_{r3} - X_{r4}) \ if \ (R_{d} < P_{a}) \& (FDR_{d} \le \varepsilon) \\ X_{d} & R_{d} > P_{a} \end{cases}$$
(17)

C. New selection technique

In CCSA, old solution X_d and new solution $X_{d,new}$ (where $d=1, ..., N_p$) are compared fitness function and better one with less fitness function will be retained as the meaning of the two following formulas:

$$X_{d} = \begin{cases} X_{d,new} & \text{if } FT_{d,new} \leq FT_{d} \\ X_{d} & \text{otherwise} \end{cases}, d = 1, \dots, N_{p}$$

$$(18)$$

$$FT_{d} = \begin{cases} FT_{d,new} & \text{if } FT_{d,new} < FT_{d} \\ FT_{d} & \text{otherwise} \end{cases}, d = 1, \dots, N_{p}$$

$$(19)$$

where FT_d and $FT_{d,new}$ are the fitness values of X_d and $X_{d,new}$.

In the proposed ASCSA, the selection technique based on eqs. (18) and (19) is only employed after the first generation via technique of Lévy fights and it would not be used after the second generation at the end of each iteration. At the moment, if the selection of pair comparison between the old solution and the new solution at the same nest continues to be employed, there will be a possibility that a better solution at another nest will be abandoned while a worse solution at the nest is certainly retained. As pointed out the disadvantage of the pair comparison in eqs. (18) and (19), we propose a new selection technique as the three following steps:

Step 1: Each old solution X_d and new solutions are grouped into one

Step 2: Arrange the order of all the solutions in the new group so that the best solution is in the first order and the worst one is in the end.

Step 3: Keep the N_p solutions which are in the leading group.

4. The Application of ASCSA for Solving the BOSTHTS Problem.

A. Initialization

In initialization procedure, N_p solutions X_d ($d = 1, ..., N_p$) is first randomly produced consisiting of decision variables $P_{si,m,d}$ and $q_{j,m,d}$ by using the two following expressions:

$$P_{si,m,d} = P_{si,\min} + rand * (P_{si,\max} - P_{si,\min}); \ m = 1, \dots, \ M \& i = 2, \dots, N_1$$
(20)

$$q_{j,m,d} = q_{j,\min} + rand * (q_{j,\max} - q_{j,\min}); m = 1, ..., M - 1 \& j = 1, ..., N_2$$
(21)

It is clear that each solution contains power output of (N_l-1) thermal generating units over all M subintervals and discharged water of N_2 hydro turbines over (M-1) subintervals. The selection aims to determine dependent variables and deal with all constraints so that solutions are valid and own acceptable fitness values. The detail of dealing with equality constraints can refer to the next section.

B. Handling real power balance constraint and available water volume constraint

Penalty method for dealing with equality constraints in application of meta-heuristic algorithms to optimization problems plays an important role resulting in valid solutions with

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expected fitness. This is totally different from the application of deterministic algorithms using maximum error as a major termination condition. Thus, selection of decision variables in each solution is one of the significant factors for finding solutions of the considered problem. In the section, step by step for obtaining dependent variable and handling equality constraints is shown and explained in detail as follows:

By using (21), discharged water via hydro turbines over the first (M-1) subintervals are known and are substituted into (9) for obtaining discharged water of the Mth subinterval as follows:

$$q_{j,M} = (W_j - \sum_{m=1}^{M-1} t_m q_{j,m}) / t_M$$
(22)

All discharged water are substituted into (10) for calculating power output of all hydro units as the following formula:

$$P_{hj,m} = \frac{-b_{hj} \pm \sqrt{b_{hj}^2 - 4c_{hj}(a_{hj} - q_{j,m})}}{2c_{hj}}; m = 1, ..., M; j = 1, 2, ..., N_2$$
(23)

As a result, power output of all hydro units and thermal units excluding the first thermal unit are known. Thus, the power output of the first thermal unit needs to be determined by using the following model:

$$P_{s1,m} = P_{D,m} + P_{L,m} - \sum_{i=2}^{N_1} P_{si,m} - \sum_{j=1}^{N_2} P_{hj,m}$$
(24)

C. Calculation of fitness function

After finding all variables of the problem, each solution in the current population must be evaluated for ranking quality and carrying out strategy of producing new solutions. Normally, evaluation criteria of solutions is performed relying on its fitness value; therefore, the fitness function must reflect the quality of solutions via objective function value and penalization values of all violations of all constraints. In the problem, the objective function is F function in eq. (1) and the term penalizations are the power output of thermal unit 1 and the discharged water at the last subinterval. Consequently, the configuration of fitness function includes the terms as shown in eq. (25).

$$FT_{d} = \sum_{m=1}^{M} \sum_{i=1}^{N_{1}} F(P_{si,m,d}) + K_{s} \sum_{m=1}^{M} (ViolationP_{s1})^{2} + K_{q} \sum_{j=1}^{N_{2}} (Violationq_{M})^{2}$$
(25)

Where K_s and K_q are punishment coefficients; and *ViolationP_{s1}* and *Violationq_M* are the punishment values corresponding to limitation violation of power of thermal unit 1 and discharged water of all hydro unit at the last subinterval.

$$ViolationP_{s1} = \begin{cases} P_{s1,m,d} - P_{s1,max} & \text{if } P_{s1,m,d} > P_{s1,max} \\ P_{s1,min} - P_{s1,m,d} & \text{if } P_{s1,m} < P_{s1,min} \\ 0 & \text{else} \end{cases}$$
(26)

$$Violationq_{M} = \begin{cases} q_{j,\max} - q_{j,\max} & \text{if } q_{j,M,d} > q_{j,\max} \\ q_{j,\min} - q_{j,\max} & \text{if } q_{j,M,d} < q_{j,\min} \\ 0 & \text{else} \end{cases}$$
(27)

D. New solution generations

As shown in section 3, there are two times new solutions generated in which the first time is done via Lévy flight random walk in section 3.A and the second time is done via the proposed adaptive selective random walk in section 3.B.

E. Fixing new solutions

As updating values for new solutions, its decision variables can be outside allowable operating values. Thus, the two following formulas are applied for fixing the violation

$$q_{j,m,d} = \begin{cases} q_{j,m,d} & \text{if } q_{j,\max} \ge q_{j,m,d} \ge q_{j,\min} \\ q_{j,\max} & \text{if } q_{j,m,d} > q_{j,\max} ; j = 1,...,N_2; m = 1,...,M - 1 \\ q_{j,\min} & \text{else} \end{cases}$$

$$P_{si,m,d} = \begin{cases} P_{si,m,d} & \text{if } P_{si,\max} \ge P_{si,m,d} \ge P_{si,\min} \\ P_{si,\max} & \text{if } P_{si,\max} > P_{si,\max} ; i = 2,...,N_1; m = 1,...,M \\ P_{si,\min} & \text{else} \end{cases}$$
(29)

F. Iterative algorithm termination condition

The whole search algorithm is terminated in case that current iteration G equals the maximum iteration G_{max} .

G. The whole search procedure of ASCSA for finding solutions of the considered problem

The whole search process of the proposed ASCSA for the considered problem is shown in the flowchart of Figure 1.



Figure 1. The flowchart of applying the proposed method for finding solutions of the considered problem

5. Numerical Results

In the section, two systems with different form of electric generation cost and polluted emission functions are employed to test the performance of the ASCSA. System 1 with convex form for both fuel and emission functions while system 2 with nonconvex form for electric generation cost and exponential form for emission can challenge the effectiveness of the ASCSA. The detail of the result is as follows. Besides, CCSA [9] and MCSA [13] are also coded for finding solutions of the two considered systems for result comparison. The proposed method together with CCSA and MCSA are searching solutions fifty times for each case by using the same Matlab platform and the same computer with Processor 2 GHz and Ram 2 GB.

A. Test system 1

In this section, system 1 consisting of two thermal and two hydro units planed in three eighthour subintervals [5] is employed to test the performance of ASCSA when compared to CCSA and MCSA, and other methods. In this case, second order equations are used for electric generation cost and emission functions.

For implementation of the applied methods, $N_p = 30$ and $G_{max} = 70$ are used for three dispatch cases while probability P_a is set to nine values ranging from 0.1 to 0.9 with a change of 0.1. In addition, the tolerance values of ASCSA is set to five values from 10^{-1} to 10^{-5} for the first dispatch case of economic dispatch and then the best value will be reused for the two remaining dispatch cases. The results obtained by such three applied methods for the economic and emission dispatch cases with respect to minimum fitness, average fitness, maximum fitness, standard deviation of 50 fitness values and computation time on average are respectively reported in Table 1 and Table 2. For economic dispatch, ASCSA has obtained the best cost equal to \$64606.0036 at different values of P_a such as 0.6, 0.7, 0.8 and 0.9 and at different values of tolerance such as 10^{-2} and 10^{-3} and 10^{-4} ; however, the best standard deviation equal to 0.0071 is only obtained at $P_a=0.8$ and tolerance=10⁻². Consequently, 10⁻² is the best value of tolerance and it will be applied for the rest of cases in the paper while P_a is always tested in the predetermined range from 0.1 to 0.9. On the contrary, the best costs from CCSA and MCSA are respectively \$64606.3218 and \$64606.311 obtained only at P_a =0.8. Other values of P_a could not lead to the same cost or less cost for CCSA and MCSA. The result can indicate that ASCSA can reduce by \$0.3182 and \$0.3074 compared to CCSA and MCSA for the best cost, and can reduce by \$10.7103 and \$7.0844 compared to CCSA and MCSA for the maximum cost. Furthermore, all fifty trial runs by ASCSA nearly have obtained the same value, which is very close to the best cost since the standard deviation cost is 0.0071. This figure is opposite for CCSA and MCSA when their standard deviations are respectively 1.7573 and 1.4373. The comparisons have pointed out that ASCSA can improve the best optimal solution and the stabilization of search ability significantly compared to CCSA and MCSA for the economic dispatch. The superiority of ASCSA over CCSA and MCSA in terms of solution quality continues to be demonstrated via the best emission shown in Table 2

dispatch of system 1								
Method	CCSA	MCSA	ASCSA					
Min. cost (\$)	64 606.3218	64 606.311	64 606.0036					
Avg. cost (\$)	6 4 608.7512	64 609.563	64 606.0090					
Max. cost (\$)	64 616.7139	64 613.088	64 606.0460					
Std. dev. (\$)	1.7573	1.4373	0.0071					
Avg. time (s)	0.2	0.2	0.2					

Table 1. The result comparisons obtained by three CSA methods for economic dispatch of system 1

The exact computation resulting in a difference emission between ASCSA and CCSA, and ASCSA and MCSA are respectively 2.7933lb and 2.4697lb for the best emission while those are respectively 6.6322lb and 9.8654 for average emission. It is clear that ASCSA is more effective than both CCSA and MCSA for the case of emission dispatch. The fitness convergence

characteristic for the economic and emission dispatch cases depicted in Figure 2 and Figure 3 have illustrated the whole search of the best solution and have resulted in a conclusion that the proposed method is faster convergent to the best solution than both CCSA and MCSA for the two cases and the improvement here is great.

Method	CCSA	MCSA	ASCSA	
Min. emission (lb)	567.6078	567.2842	564.8145	
Avg. emission (lb)	571.4467	574.6799	568.5481	
Max. emission (lb)	576.3903	589.7284	581.4021	
Std. dev. (lb)	2.1250	3.9628	2.9747	
Avg. time (s)	0.2	0.2	0.2	

Table 2. The result comparisons obtained by three CSA methods for emission dispatch of system 1



Figure 2. Fitness values obtained by three CSA methods for fuel cost objective of the first system



Figure 3. Fitness values obtained by three CSA methods for emission objective of the first system



Figure 4. The set of non-dominated solutions and the best solution obtained by the proposed method for two objective case of the first system.

Method	Economic dispatch		Emission of	dispatch	Bi-objective dispatch			
Wiethou	Cost (\$)	Time (s)	Emission(lb)	Time (s)	Cost (\$)	Emission (lb)	Time (s)	
RC-GA[5]	66 031	21.63	586.14	20.27	-	-	-	
NS-GA[5]	-	-	-	-	66 331	618.08	27.85	
MO-DE [5]	-	-	-	-	66 354	619.42	30.71	
SPEA[5]	-	-	-	-	66 332	618.45	34.87	
CPSO - PM[7]	65 741	18.25	585.67	18.00	65 821	620.78	18.98	
CPSO [7]	65 241	18.32	579.56	18.31	65 731	618.78	19.31	
PPA-PM [7]	64 873	16.14	572.71	15.93	65 426	612.34	16.53	
PPA [7]	64 718	15.99	569.73	15.18	65 104	601.16	16.34	
PPA-PSA-PM[7]	64 689	15.98	568.78	15.92	65 089	600.24	16.15	
PPA-PSA [7]	64 614	15.89	564.92	15.45	65 058	594.18	16.74	
CCSA	64 606.3	0.2	567.61	0.2	65 054.601	594.474	0.2	
MCSA	64 606.3	0.2	567.28	0.2	65 052.004	594.594	0.2	
ASCSA	64 606.0	0.2	564.72	0.2	65 053.899	594.045	0.2	

Table 3. Comparisons for the first system with three dispatch cases

For the bi-objective optimization case, there are 22 non-dominant solutions obtained by different values for Ψ_1 and Ψ_2 while satisfying eqs. (4) and (5). The most suitable solution is then obtained by using the Fuzzy based technique [17-18]. Finally, the Pareto curve has been obtained and depicted in Figure 4 and the best compromise has been also pointed out based on the highest value of the cardinal priority. The way to obtain the best compromise for CCSA and MCSA has also been carried out similarly. As a result, the fuel cost and emission yielded by ASCSA has been compared to those from other reported in Table 3. The fuel cost comparison and emission comparison has pointed out that ASCSA has obtained the best optimal solution for economic

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dispatch and the best optimal solution for emission dispatch compared to all methods. In fact, the cost and the emission by ASCSA are \$64,606.0 and 564.72lb while the values from the best PPA-PSA method in [7] are respectively \$64,614 and 564.92lb, and those from the worst RC-GA method in [5] are \$66,031 and 586.14lb. It is clear that ASCSA can reduce to \$8 and 0.2lb compared to PPA-PSA, and \$1425 and 21.42lb compared to RCGA. For the bi-objective optimization case, ASCSA can obtain better cost and emission than CCSA; however, there is a trade-off between the fuel cost and emission yielded by MCSA and ASCSA since ASCSA has obtained worse cost but better emission. Compared to the rest of methods, ASCSA can save \$1,300 and 25lb compared to the worst MO-DE method in [5] and \$4 and 0.135lb compared to the best PPA-PSA method in [7]. Furthermore, the execution time from the proposed ASCSA is the fastest equal to 0.2 second while other ones have spent much more time from 15.45 seconds to 34.87 seconds. As a result, it can give a conclusion that ASCSA is the best method compared to all methods since it has obtained the best cost and emission with the fastest execution time.

B. Test system 2

The second system with two hydro and four thermal units over four subintervals with twelve hours for each considering non-convex electric generation cost function and an exponential form of polluted emission function is used as a test system [5]. For application of such three CSA methods, $N_p = 50$ and $G_{max} = 300$ are taken for CCSA and MCSA while $N_p = 50$ and $G_{max} = 200$ for the proposed method. The result comparisons reported in Table 4 for the system see that ASCSA has obtained the best fuel cost of \$64,728 for economic dispatch and 22,818.3 lb for emission dispatch while those from CCSA are respectively \$65,243 and 22,821.3 lb, and those from MCSA are respectively \$64,889 and 22,822.2 lb. The exact computation indicates that the cost from ASCSA is less than CCSA and MCSA by \$515 and \$161. Equally, the emission from ASCSA is also lower than that from CCSA and MCSA by 3 lb and 3.9 lb. Note that both CCSA and MCSA have been slowly convergent to optimal solutions by setting G_{max} =300 while ASCSA has spent only 200 iterations. The lower number of iterations leads to the faster execution time from ASCSA compared to CCSA and MCSA. In fact, that from ASCSA is under one second while that is around 1.5 seconds for CCSA and is around 2.3 seconds for MCSA. The superiority of the proposed ASCSA method over CCSA and MCSA continues to be reflected by the fitness convergence characteristic shown in Figure 5 and Figure 6. It can be seen that the proposed method is always faster convergent than two others. Among the methods in the studies [3], [5-8], PPA-PSA is still the best one with the lowest fuel cost and emission for all the dispatch cases. The method has obtained the best cost of \$65,567 for economic dispatch and the best emission of 22,828 lb for emission dispatch, and \$66,951 and 25,596 lb for electric generation cost and polluted emission of the two -objective optimization case. Although the results yielded by PPA-PSA are promising compared to other ones, these values are higher than those from ASCSA. The exact computation reports that ASCSA can reduce amount of money and amount of emission max for economic and emission dispatch cases compared to the method by \$837 and 9.7 lb. For the bi-objective optimization case, ASCSA continues to reduce by \$415 and 952 lb. Clearly, the reduction of fuel cost and emission yielded by ASCSA is not low compared to PPA-PSA. Consequently, it can be confirmed that ASCSA has obtained better quality of optimal solutions than all considered methods. Furthermore, the execution time reported in Table 4 also sends a message that ASCSA is much faster than all methods. The methods in [3] and [6] were coded in a Pentium III computer but computers used in studies [5], [7] have not been mentioned. Finally, based on the evidences of high quality solutions and shorter simulation time, it can lead to a conclusion that ASCSA is very efficient for solving the problem with two objective functions consisting of fuel cost and emission where valve effects are taken into account.

	Economic dispatch		Emission	dispatch	Bi-objective dispatch		
Method	Cost (\$)	CPU (s)	Emission (lb)	Time (s)	Cost (\$)	Emission (lb)	Time (s)
SAA[3]	70 718	-	23 200	-	73 612	26 080	1492
RC-GA[5]	66 516	40.36	23 222	41.98	-	-	-
NS-GA[5]	-	-	-	-	68 333	25 278	45.42
MO-DE [5]	-	-	-	-	68 388	25 792	46.76
SPEA [5]	-	-	-		68 392	26 005	57.02
GA- UM [6]	67 751	90.15	23 223	78.27	68 521	26 080	96.10
EGA- UM[6]	66 539	51.63	23 223	42.87	68 492	26 080	53.54
CPSO - PM [7]	66 349	33.14	23 167	33.63	67 994	25 902	34.11
CPSO [7]	66 223	32.15	23 112	32.34	67 892	25 773	34.52
PPA-PM [7]	65 912	21.03	23 078	21.18	67 211	25 606	22.04
PPA [7]	65 885	21.45	22 966	21.56	67 170	25 601	22.11
PPA-PSA-PM [7]	65 723	21.12	22 912	24.74	67 092	25 600	24.90
PPA-PSA[7]	65 567	22.00	22 828	21.98	66 951	25 596	22.76
IM-MODA [8]]	68 000	-	23 031.57	-	-	-	-
CCSA	65 243	1.54	22 821.3	1.6	66 733	24 667	1.6
MCSA	64 889	2.3	22 822.2	2.2	66 698	24 727	2.3
ASCSA	64 728	0.96	22 818.3	0.97	66 536	24 644	0.99

 Table 4. Comparisons for system 2 with non-convex electric generation cost and exponential emission functions



Figure 5. Fitness values obtained by three CSA methods for fuel cost objective of the second system



Figure 6. Fitness values obtained by three CSA methods for emission objective of the second system

6. Conclusions

The paper has proposed an adaptive selective cuckoo search algorithm for finding optimal solutions of the bi-objective hydrothermal power system optimization operation problem considering short term. The ASCSA has been implemented for dealing with two systems with different fuel cost functions and different emission functions. In the first system, the objective is represented as second order fuel cost and emission functions but the objective is represented as nonconvex fuel cost function and convex emission function in the second system. The performance of ASCSA compared to original CSA and another modified version has indicated that ASCSA is superior to such two methods with respect to optimal solution quality and convergence time. The figure of comparisons is also the same when compared to other methods. Consequently, it can result in a conclusion that ASCSA is a strong optimization tool for finding solutions of the considered problem.

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APPENDIX

Table A1. Power output of thermal units and hydro units found by the proposed method for the first test system

			-20002025			
Case	Sub- interval	P_D (MW)	P_{sl} (MW)	P _{s2} (MW)	P_{hl} (MW)	$\begin{array}{c} P_{h2} \\ (\mathrm{MW}) \end{array}$
Economic dispatch	1	900	168.6634	415.9205	245.3948	98.5524
	2	1200	219.1281	570.2793	305.4036	157.0828
	3	1100	202.1743	518.4747	285.2499	137.3699
Emission dispatch	1	900	299.9557	359.1235	213.0055	59.9468
	2	1200	299.9728	434.9514	330.9877	188.3681
	3	1100	299.8197	415.1421	289.3711	141.2896
Bi-objective optimization	1	900	230.3217	372.7074	237.1016	89.3736
	2	1200	289.7870	488.0614	311.7070	163.6907
	3	1100	269.9159	448.4597	286.7235	139.3812

				1				
Case	Sub.	P_D (MW)	P _{s1} (MW)	P _{s2} (MW)	P _{s3} (MW)	P _{s4} (MW)	P _{h1} (MW)	P _{h2} (MW)
Economic dispatch	1	900	99.074	30.179	125.065	139.795	175.171	346.455
	2	1100	98.647	30.000	124.977	229.506	216.244	424.244
	3	1000	98.574	30.000	40.000	229.494	242.226	379.766
	4	1300	98.554	112.675	209.832	229.606	243.064	438.760
	1	900	72.376	133.715	136.053	91.508	167.833	314.330
Emission	2	1100	78.874	141.821	147.592	100.161	249.623	405.876
dispatch	3	1000	75.419	137.437	142.303	95.598	208.030	360.863
	4	1300	101.826	167.785	184.864	129.322	249.996	500.000
Bi-objective optimization	1	900	98.523	112.683	124.935	50.076	185.955	344.091
	2	1100	98.536	112.699	124.919	139.769	244.179	403.679
	3	1000	98.534	112.667	124.894	139.762	196.680	346.885
	4	1300	98.537	146.090	209.813	139.768	249.796	489.397

Table A2. Power output of thermal units and hydro units found by the proposed method for the second test system



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