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A Statistical Analysis of Ranking Artificial Bee Colony Algorithm for Solving Bi-Objective Hydrothermal Scheduling Problem

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Abstract: This paper delineates an experimental framework to confirm the distinctiveness of artificial bee colony (ABC) algorithm for hydrothermal scheduling (HTS) problems. The experimental framework can be involved in two main phases: one is the optimal generation allocation of hydrothermal power system using an ABC algorithm in proportion to the compromised fuel cost (FC) and emission release (ER). In which the HTS problem is formulated as a bi-objective framework with an intricate equality and inequality constraints. A linear interpolated price penalty factor approach is exercised for blending two objectives concurrently. Meanwhile, solution repair strategy is incorporated in the algorithm that handles the control variable in turn to satisfy water dynamic and system equality constraints. The applicability of the ABC algorithm is demonstrated on cascaded hydrothermal system. Second is the standard statistical test carry out using SPSS software for comparing the results that were obtained by the proposed and other techniques have considered in the literature. The experimental results confirm that the ABC algorithm shows significant distinctive than other techniques while performing energy, economic and environmental impact assessment on the hydrothermal power system.

Key words: Hydrothermal Scheduling · Economic/Emission · Artificial Bee Colony Algorithm · One-Way ANOVA · Nonparametric Test

INTRODUCTION

Hydrothermal scheduling is an optimization problem that derives an operating strategy for minimizing not only fuel cost of thermal power generation but also secures the phenomenal exhausting of fossil fuel resources through the optimum utilization of the available hydro resource; these are the major sources of atmospheric pollution. Therefore, the amalgamated optimal dispatch of hydrothermal generating units is to be considered a great importance in power system operation. It has devised as short-term scheduling problem subjected to operational constraints of both thermal and hydro units are fully satisfied. Usually, the power generation of each hydro plant is computed using optimal water discharge and storage volume. In the cascaded reservoir configuration, water inflow to the successive reservoir depends on its forerunner reservoir discharge rate and storage volume. It builds a dynamic relation among water inflow, discharge and storage. Therefore, finding optimal generation schedule for hydrothermal system effectively is a significant challenge to the scheduler [1].

Many metaheuristic algorithms have been evolved for solving HTS problem from the past decade in which differential evolution (DE) [2] multi-objective differential evolution (MO-DE) [3] particle swarm optimization (PSO) [4] are widely employed to attain optimal generation scheduling intent of obtaining minimum emission release and energy efficient operation subjected to operational and physical constraints of thermal and hydro plants. While strictly satisfying all constraints of the test system, evolutionary computation approaches often converge to sub-optimal solution prematurely. To ensure high-quality solution near to global optima various heuristic techniques have combined themselves or with any operator to develop hybrid optimization method. Some of them are an interactive fuzzy satisfying method based on evolutionary programming technique [5] self-organizing

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hierarchical particle swarm optimization technique with time-varying acceleration coefficients (SOHPSO_TVAC) [6] civilized swarm optimization (CSO) [7] simulated annealing based multi-objective cultural differential evolution (SA-MOCDE) [8] improved gravitational search algorithm (IGSA) [9] dynamically controlled particle swarm optimization (DC-PSO) [10] hybrid chemical reaction optimization (HCRO) [11] improved multi-objective gravitational search algorithm (IMOGSA) [12] and surrogate differential evolution (SDE) [13].

As far as the state-of-the-art, literature the HTS has devised either Bi or multi-objective combinatorial optimization that has non-convex objective function and solved using numerous metaheuristic optimizations. However, the reported optimization techniques had found an optimum solution; it is not an end global solution to HTS problem due to the common shortcomings of algorithm complexity, premature convergence (because of imbalance between exploration and exploitation) and large computational time. To overcome this drawback, a new emerging optimization tool, i.e., an artificial bee colony (ABC) algorithm is preferred with the suitable control parameter. Moreover, four distinctive selections process balance intensification and diversification. The superior convergence characteristics and performance of the ABC algorithm than other swarm intelligence techniques, while solving a set of standard test functions have been successfully analyzed [14, 15]. In order to serve electricity at the cheapest possible price with cleanliness, environment a suitable optimum operation strategy was developed in the author's earlier research work using an ABC algorithm. In which the optimum utilization of fossil fuel minimize the fuel cost and emission release that protect the environmental damage [16].

In recent decades, many evolutionary and swarm intelligence algorithms have been employed to solve bi-objective or multiobjective hydrothermal scheduling problem the simulation results show that they outperform each other numerically. In this situation, the use of standard statistical analysis improves the evaluation process of the performance of a new algorithm that has become necessary to confirm whether a new proposed method offers a significant improvement, or not, over the existing methods for a given problem.

Ahadzie *et al*. [17] has carried out one sample t-test to analysis the data and the descriptive statistics provide interesting findings such as minimum, maximum, mean, standard deviation and standard error. Further, each attribute was ranked according to its standard deviation to help provide a clearer picture of the consensus reached by the respondents. The behavior of different evolutionary algorithms' over optimizing a set of standard test function has been distinguished using parametric and non-parametric statistical tests [18]. An advanced experiment has conducted in computational intelligence and data mining for multiple comparisons, respectively [19, 20]. Followed, Derrac *et al*. [20] has exercised a practical tutorial on the use of the non-parametric statistical test for comparing evolutionary and swarm intelligence algorithms [21]. The null hypothesis significance test has performed for the comparison and ranking of evolutionary algorithms [22] whilst the swarm intelligent behavior was analyzed in solving multiobjective optimization [23].

In this paper, a strategy for bi-objective hydrothermal optimization based upon the behavior of an artificial bee colony algorithm has presented where the linear interpolated price penalty factor approach is incorporated. The control parameter of ABC is tuned to ferret out the cost-effective/environmentally sustainable schedule for the cascaded hydrothermal system that consists four hydro and three thermal units. Descriptive, parametric and nonparametric tests are conducted wherein the solution that has obtained already by several algorithms in the same test system is used from the literature. With the aim the paper is structured into six sections. The objective function and constraints are briefed in section 2 whereas, an overview and implementation of the proposed ABC algorithm, including the constraint handling mechanism has been described in section 3. The statistical analysis is explained in the next section. Followed, the computation and experimental results obtained by the ABC algorithm is illustrated in section 5. At last, the inference is summarized in section 6.

Problem Formulation: The fuel cost and emission release of the thermal unit have considered as objective functions of HTS problem. These are the function of real power generation and have to be minimized concomitantly. The mathematical expression is:

$$\text{Minimize } \{F(P_{si,k}), E(P_{si,k})\} \tag{1}$$

The cost function of thermal units over a scheduling period can be defined (2).

$$F(P_{si,k}) = \sum_{k=1}^{T}\sum_{i=1}^{N_s} t_k \Big[a_i + b_i P_{si,k} + c_i P_{si,k}^2 + \left| d_i \sin\left\{ g_i \left(P_{si}^{\min} - P_{si,k} \right) \right\} \right| (\$) \Big] \tag{2}$$

The emission produced by the thermal units is a supplement to the usual cost function and can be defined (3).

$$E(P_{si,k}) = \sum_{k=1}^{T}\sum_{i=1}^{N_s} t_k \left[\alpha_i + \beta_i P_{si,k} + \gamma_i P_{si,k}^2 + \eta_i \exp\left(\delta_i P_{si,k}\right) e_{i,k}\left(P_{si,k}\right) \right] \text{ (lb)} \tag{3}$$

Subjected to the subsequent operational and physical constraints of hydro and thermal plants, in which some of them impose either equality or inequality relationship:

The power balance constraint of HTS problem is mathematically formulated (4).

$$\sum_{i=1}^{N_s} P_{si,t} + \sum_{j=1}^{N_h} P_{hj,t} - P_{D,t} - P_{L,t} = 0 \tag{4}$$

where,

$$P_{L,t} = \sum_{i=1}^{N_s+N_h}\sum_{j=1}^{N_s+N_h} P_{i,t} B_{ij} P_{j,t} + \sum_{i=1}^{N_s+N_h} B_{oi} P_{i,t} + B_{oo} \tag{5}$$

$$P_{hj,t} = C_{1j} V_{hj,t}^2 + C_{2j} Q_{hj,t}^2 + C_{3j} V_{hj,t} Q_{hj,t} + C_{4j} V_{hj,t} + C_{5j} Q_{hj,t} + C_{6j} \tag{6}$$

The initial and final storage volume of the reservoir is modeled as equality constraint and given by (7).

$$V_h(j,t)|^{t=0} = V_h(j)^{begin} ; V_h(j,t)|^{t=T} = V_h(j)^{end} \tag{7}$$

Neglecting spillage the hydraulic continuity equation is modeled (8).

$$V_h(j,t+1) = V_h(j,t) + I_h(j,t) - Q_h(j,t) + \sum_{m=1}^{R_u}\sum_{t=1}^{T} Q_h(m, t-\tau) \tag{8}$$

The power generation at an each interval has met the following inequality constraints:

$$P_{si}^{\min} \le P_{si,t} \le P_{si}^{\max} \qquad i = 1,2,....N_s \tag{9}$$

$$P_{hj}^{\min} \le P_{hj,t} \le P_{hj}^{\max} \qquad j = 1,2,....N_h \tag{10}$$

Similarly, the water discharge and reservoir storage volume at an interval have satisfied its lower and upper limits and is represented in (11) and (12) respectively.

$$Q_{hj}^{\min} \le Q_{hj,t} \le Q_{hj}^{\max} \qquad j = 1,2,....N_h \tag{11}$$

$$V_{hj}^{\min} \le V_{hj,t} \le V_{hj}^{\max} \qquad j = 1,2.....N_h \tag{12}$$

Handling Bi-Objective: Unlike the single objective optimization, bi-objective optimization problems deal with two objective functions that are competing and conflicting. Generally, it can be handled by using the price penalty factor approach. The price penalty factor is defined as the ratio between the average full load fuel cost and average emission of the corresponding generator as its maximum output.

Computation of modified price penalty factor:

Step 1: The computation of $h_{\max}$:

$$h_{\max} = \frac{F\left(P_{si}^{\max}\right)}{E\left(P_{si}^{\max}\right)} \tag{13}$$

Step 2: According to $h_{max,}$ the thermal units were ranked in rising order.

Step 3: Then the maximum limit of each unit was added one at a time starting from the lowest h_{max} until $\sum P_{si}^{\max} \ge P_{D,k}$ have been discerned.

Step 4: In this procedure h_{max} related to the last unit was considered as a price penalty factor to trade-off two conflict objectives.

Computation of Normalized Price Penalty Factors: While performing *step 3* sum of the maximum capacity of thermal units often greater than demand, it may lead approximate value. In order to determine the non-inferior solution, an accurate model is necessary which is not explored in the literature. This drawback can be rectified by incorporating a simple mathematical technique with the usual procedure.

Let, P_{g1} is the maximum capacity of a unit at that moment by adding the same causes sum total exceeds the load demand P_D and its corresponding price penalty factor is h_1. The maximum capacity P_{go} is the predecessor and the associated price penalty is h_o. Then the normalized price penalty factor can be determined using the (14).

$$h_k = h_o + \left(\frac{h_1 - h_o}{P_{s1} - P_{so}}\right) * \left(P_{D,k} - P_{so}\right) \tag{14}$$

Now, the simultaneous objective function is modeled by using h_k and then the function to be minimized is defined as,

$$\text{Minimize } \{F(P_{si,k}) + h_k * E(P_{si,k})\} \quad (15)$$

Application of ABC to Hts Problem

Overview: It is a bio-inspired swarm intelligent algorithm and developed by Karaboga in 2008 by inspiring the intelligent foraging behavior of real honey bees. The colony of real honey bees consists of three groups; employed bees, onlooker bees and scout bee. The fascinating significances of the honey bees are self-organization and division of labor. These are enough to get a solution in the search space. A waggle dance is a mechanism of honey bees used to perform during food foraging task, through which information about all the current rich sources is exchanged and allowed to decide the most profitable source. Based on these an artificial bee colony algorithm was mathematically modeled. Basically, ABC algorithm has been carried out; Initialization Phase, Employed Bees Phase, Onlooker Bees Phase and Scout Bees Phase with few control parameters.

Pseudo-Code of ABC Algorithm: The four different selection processes that carry by the ABC algorithm in the feasible search space are presented in the form of pseudo-code as follows:

Step 1: Initialize the population of solutions using (16).

$$x_{k,l} = x_{k,l}^{\min} + rand[0,1]\left(x_{k,l}^{\max} - x_{k,l}^{\min}\right) \quad (16)$$

Step 2: Population is evaluated.

Step 3: FOR cycle = 1; REPEAT

Step 4: New solutions (food source positions) v_{kl} in the neighborhood of x_{kl} are produced for the employed bees using (17) is the solution in the i^{th} neighborhood, *rand (k, l)* being a random number (-1 = rand = 1) and evaluate them.

$$v_{k,l} = x_{k,l} + \phi_{k,l}\left(x_{k,l} - x_{m,l}\right); \quad k \neq m; m \in SP; l \in D \quad (17)$$

Step 5: Store the best values between x_{kl} and v_{kl} after the greedy selection process.

Step 6: Probability values p_k for different solutions of x_k are calculated by means of their fitness values using (18). In this *fit* represents the fitness values of solutions and these are calculated using (19).

$$p_k = \frac{fit_k}{\sum_{m=1}^{SP} fit_m} \quad (18)$$

$$fit_k = \begin{cases} \dfrac{1}{1+f(x_k)} & if\ f(x_k) \geq 0 \\ 1 + abs(f(x_k)) & if\ f(x_k) < 0 \end{cases} \quad (19)$$

Step 7: Based on probabilities (p_k), new solutions v_k for the onlooker is produced from x_k.

Step 8: REPEAT Step-5.

Step 9: Next, the abandoned solution is determined if exists and it is replaced with a newly produced random solution x_i for the scout as explained in scout bee phase i.e., using (16).

Step 10: Memorize the best food source obtained so far.

Step 11: Cycle = cycle+1

Step 12: UNTIL cycle = Maximum;

Step 13: STOP

The implementation procedure of an ABC algorithm for HTS have been summarized in this section.

Initialization of Control Variables: There are two sets of control variables, one is hourly water discharge of hydro plant and another is the thermal generation denoting the current food set of the population to be evolved. These are randomly engendered within the operational limits based on (20) and (21).

$$Q_{h,jk} = Q_{hj}^{\min} + rand * \left(Q_{hj}^{\max} - Q_{hj}^{\min}\right) \quad (20)$$

$$P_{s,ik} = P_{si}^{\min} + rand * \left(P_{si}^{\max} - P_{si}^{\min}\right) \quad (21)$$

Unlike thermal generation, the hourly hydro discharge should be satisfied hydraulic dynamic constraints, initial and final reservoir volume constraints. In order to handle above-mentioned constraints, a solution repair mechanism is adopted in the algorithm.

Therefore, a dependent interval "d" was chosen randomly and discharge at that interval was calculated by re-arranging (8) and given by (22), until (11) is satisfied otherwise hydrogenation was computed using (6) with the available storage volume of water and satisfied water discharge.

$$Q_{hj\,d} = V_{hj}^{begin} - V_{hj}^{end} - \sum_{\substack{k=1\\k\neq d}}^{T} Q_{hj,k} + \sum_{k=1}^{T} I_{hj,k} + \sum_{u=1}^{R_u}\sum_{k=1}^{T} Q_{h(u,k-\tau)} \quad (22)$$

Then, the set of trial a vector is structured as an array to fix the position of the initial solution [SP x T* (N_h+N_s)] and are deployed for entire schedule horizon to obtain an optimum generation schedule.

$$x^{o} = \left[Q_{h11} \ldots Q_{h1T} \ldots Q_{hj1} \ldots Q_{hjT} \;\; P_{s11} \ldots P_{s1T} \ldots P_{si1} \ldots P_{siT} \right] \quad (23)$$

Fitness evaluation of augmented objective function: An augmented objective function (AOF) is derived using (24), which is the sum of the objective function considered and absolute value in violation of power balance constraint with a high valued scalar multiplier. This technique converts the primal constrained problem into an unconstrained problem.

$$AOF = \left(objective + 1000 * \left| \sum_{k=1}^{T} \sum_{m=1}^{N_s+N_h} \left(P_{m,k} - P_{Dk} - P_{Lk} \right) \right| \right) \quad (24)$$

The fitness value of all individuals of the current food set matrix (x^o) is calculated using (25), the best one is identified and stored in a memory location for the next phase.

$$fit_i = \begin{cases} \dfrac{1}{1+AOF} & if\ AOF \geq 0 \\ 1 + abs(AOF) & if\ AOF < 0 \end{cases} \quad (25)$$

Updating food position for an optimal solution: The new position of each food source, if $Q_{hj,\,k}$ and $P_{si,\,k}$ violate their allowable ranges and they are limited to their respective ranges.

$$x_i^{',new} = x_i^{new} + rand[0\ 1] * \left(x_i^{new} - x_i^{old} \right); \quad i \in (N_s + N_h) \quad (26)$$

Likewise, the fitness value of all individuals of the updated food set matrix is calculated using (26), the best one is identified and stored in a memory location for the next phase. Then the same procedure is repeated for next phase and followed fitness evaluation is performed to identify the best solution.

Fitness evaluation of the new food source position: For the new position of each control variable, the *AOF* is calculated. Then, the best food source is memorized and unimproved food sources are abandoned using (21).

Modification of Thermal Generation Schedule: Since the hydro generation is computed from optimum water discharge and satisfied storage volume the modification of hydropower can affect the previous water discharge. Hence, all hydro and first N_s-1 thermal generations are retained at the optimum value and one thermal generation is modified to satisfy the power balance equation based on solution repair strategy. Therefore, by substituting (5) in (4) a quadratic equation as the function of P_{gd} is derived and it can be solved for the slack thermal unit that satisfies the constraint (3) perfectly.

$$B_{dd} P_{sd,k}^{2} + \left(2 \sum_{m=1}^{(N_s+N_h)-1} B_{d,m} P_{m,k} - 1 \right) P_{sd,k} + \left(\sum_{m=1}^{(N_s+N_h)-1} \sum_{n}^{(N_s+N_h)-1} P_{m,k} B_{mn} P_{n,k} + \sum_{m=1}^{(N_s+N_h)-1} B_{m,0} P_{m,k} - \sum_{\substack{m=1\\m\neq d}}^{(N_s+N_h)-1} P_{m,k} + B_{00} + P_{Dk} \right) = 0; k \in T \quad (27)$$

Inequality Constraints Handling Mechanism: The decision variables of hydro plant discharge and thermal plant output power are kept in the valid range by handling appropriately. If any newly engendered decision variable falls either behind the lower or beyond the upper limits it can be handled as follows:

$$Q_{hj,t} = \begin{cases} Q_{hj}^{\min} & if\ Q_{hj,t} < Q_{h,j}^{\min} \\ Q_{hj}^{\max} & if\ Q_{hj,t} > Q_{h,j}^{\max} \end{cases} \quad j \in N_h; t \in T \quad (28)$$

$$P_{k,t} = \begin{cases} P_{k}^{\min} & if\ P_{k,t} < P_{k}^{\min} \\ P_{k}^{\max} & if\ P_{k,t} > P_{k}^{\max} \end{cases} \quad k \in (N_h + N_s); t \in T \quad (29)$$

Evaluation of the Stopping Condition: If $iter < \max Cycle$, update food position. Otherwise, the ABC algorithm terminates.

Statistical Measures: Commonly two classes of tests are emphasized in statistical analysis to test the significant importance or the difference between two measured phenomena in addition to descriptive statistics. These are parametric tests and nonparametric tests, depending on the concrete type of data employed. In the parametric analysis, a common statistical technique repeated measures ANOVA is performed for testing the difference between more than two related sample means [18]. Whereas in nonparametric analysis pairwise statistical procedures perform individual comparisons between the two algorithms, obtaining in each application a p-value independent from another one. Pairwise comparisons are the simplest kind of statistical tests that compare the performance of two algorithms when applied to a common set of problems. In order to do the same a quick and easy procedure, Wilcoxon signed rank test is performed [19, 20].

Descriptive Statistics: Descriptive statistic is a procedure used to summarize numeric observation, organize and make sense of the population considered a specific attribute to be important or otherwise. Typically, descriptive statistics are presented in a tabular form that includes minimum, maximum and means for each attribute including the associated standard deviation and standard error [17]. In which, the standard deviation is the most frequently used indices of variability and includes every score in its calculation. Its formulation is categorized into evaluating from a population.

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}} \tag{30}$$

where x_i is the value of the i^{th} item μ is the population arithmetic mean and N is the population size.

One-Way ANOVA: The ANOVA is a statistical technique which compares different sources of variation within a data set. The purpose of the comparison is to determine if substantial differences exist between two or more groups. While doing one-way ANOVA, the following were assumed that the populations from which the samples were received must be normally or approximately normally distributed, the samples must be sovereign and the variances of the populations must be equal. Then the null hypothesis will be that all population means are equal, the alternative hypothesis is that at least one means is different. The one-way ANOVA statistical model summary provides the subsequent prediction [23].

The ANOVA partitions the total variation of the data, i.e., sums of squares (SS_T) into two sources:

- The variation that exists within each group, called the within groups sum of squares (SS_W).
- The variation that exists between the groups, called the between-groups sum of squares (SS_B).

Each SS is used to form an independent estimate of the H_0 population variance. The estimate based on the within-group variability is called the within-group variance estimate, i.e., Mean square within (MS_W). The estimate based on the between-group variability is called the between-group variance estimate, i.e., Mean square between (MS_B). Finally, an F ratio is calculated.

$$F = \frac{MS_B}{MS_W} = \frac{SS_B/df}{SS_W/df} = \frac{N-k}{k-1} \frac{\sum n\left(\bar{x} - \bar{X}_{GM}\right)^2}{\sum (n-1) S^2} \tag{31}$$

where,

x - Data value
N - Total sample mean
$\bar{X}_{GM}$ - Grand mean
$(k - 1)$ - Degree of freedom (*df*) of SS_W
$(N - k)$ - Degree of freedom (*df*) of SS_W

$$S^2 = \frac{\sum \left(x - \bar{X}_{GM}\right)^2}{(n-1)}$$

Wilcoxon Signed Rank Test: It is a nonparametric procedure employed in hypothesis testing situations, involving a plan with two samples. This is analogous to the paired t-test in nonparametric statistical procedures; thus, it is a pairwise test that purports to find important deviations between two sample means, i.e., the behavior of two algorithms. The procedure of Wilcoxon's test is reported as follows [20].

Step 1: The difference between the performance scores of the two algorithms on i^{th} out of n problems is determined and let it be d_i.

Step 2: The differences are ranked according to their absolute values; in the case of ties, ignore ties, assign the highest rank, compute all the possible assignments and average the results obtained in every application of the test and so on, although the use of average ranks for dealing with ties also recommended.

Step 3: Let R^+ be the sum of the ranks of the problems in which the first algorithm outperformed the second and R^- the sum of the ranks for the opposite. Ranks of $d_i = 0$ are split evenly among the sums; if there are an odd number of them, one is ignored:

$$R^+ = \sum_{d_i>0} rank\left(d_i\right) + \frac{1}{2}\sum_{d_i=0} rank\left(d_i\right)$$
$$R^- = \sum_{d_i<0} rank\left(d_i\right) + \frac{1}{2}\sum_{d_i=0} rank\left(d_i\right) \quad (32)$$

Step 4: Let T be the smaller of the sums, T = min (R^+, R^-). If T is less than or equal to the value of the distribution of the Wilcoxon for n degrees of freedom, the null hypothesis of equality of means is rejected; this will mean that a given algorithm outperforms the other one, with the p-value associated. Given its widespread use, the computation of the p-value for this test is usually included in well-known statistical software packages SPSS.

RESULTS AND DISCUSSION

The applicability of the ABC algorithm is examined on the cascaded hydrothermal system that has four hydro and three thermal units [5]. The operating cost and emission characteristic of the thermal unit are modeled as quadratic non-convex function. Additionally, line loss also considered that increases the intricacy of the problem and the B*mn* coefficients are referred from [3]. The total scheduling is carried for 24 hours with an hour interval.

The ABC algorithm is coded in MATLAB 7.9 platform and is simulated on an Intel (R) Core (TM) i5-4140C CPU, 1.70GHz, 4-GB RAM personal computer. To substantiate the potency of ABC algorithm, HTS problem is simulated for minimizing FC and ER simultaneously. The obtained values of the test system is compared statistically with the previous methods of DE [2] MODE [3] PSO [4] SOHPSO_TVAC [6] SA-MOCDE [8] IGSA [9] DCPSO [10] HCRO [11] IMOGSA [12] and SDE [12] to validate the solution quality.

Optimal Solution: The perspective of combined economic and emission scheduling (CEES) of hydrothermal power system addresses energy efficient utilization and environmental issues. Hence, it has in mind to minimize conflicting FC and ER. To do the same a linear interpolated price penalty factor approach is slotted in with an ABC algorithm to obtain a trade-off between these objectives and the corresponding normalized price penalty factor for a certain load demand and have been listed in Table 1. Thus, a trade-off has been obtained between FC and ER at $ 42109.8738 and 9402.3019 (lb) respectively. Followed, the optimum water utilized for minimum FC and ER is presented in Table 2. Consequently, hourly optimal hydro plant generation scheduling and thermal generation scheduling have been shown in Figures 1 and 2 respectively. Further, from the Figure 3, it is viewed that the water storage volume during the scheduling period is satisfied with its limits at each interval. Moreover, the water transportation trajectory of reservoirs has begun its initial volume and terminated at exact final value, which substantiates the constraint handling mechanism and ABC's search ability.

Table 1: Price penalty factor for particular load demand

Hr	PD (MW)	Price penalty factor
1	750	1.4850
2	780	1.7443
3	700	1.3760
4	650	1.0699
5	670	1.1484
6	800	1.7845
7	950	1.9673
8	1010	2.5961
9	1090	2.9555
10	1080	2.9158
11	1100	2.6127
12	1150	2.4092
13	1110	2.1786
14	1030	2.5956
15	1010	2.1736
16	1060	2.4625
17	1050	2.8194
18	1120	2.8144
19	1070	2.9812
20	1050	2.6992
21	910	1.9126
22	860	1.7957
23	850	1.6881
24	800	1.5400

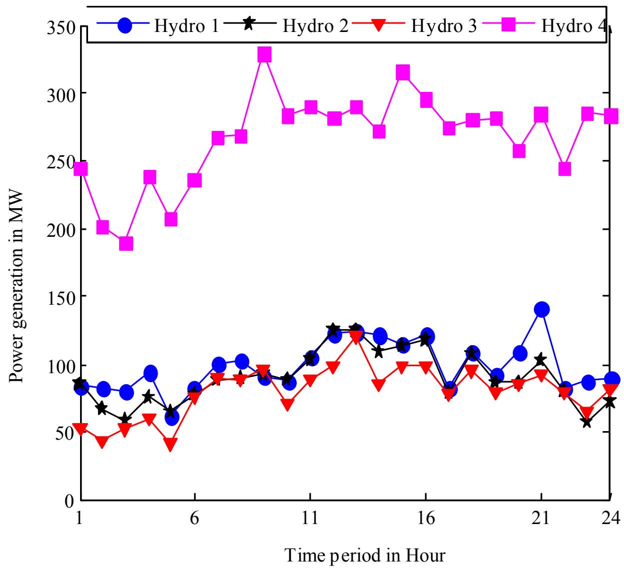

Fig. 1: Hourly optimal hydro plant generation obtained by ABC for CEES

Table 2: Hourly Optimal water discharge obtained by ABC for CEES

Water Discharge 10^4 m^3									
Hr	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}	Hr	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}
1	8.5356	7.5667	27.8900	6.0000	13	6.7306	6.8285	10.4628	16.8206
2	7.6805	8.1147	19.3668	6.0000	14	11.3490	10.0775	12.3911	7.2588
3	8.0546	7.2890	10.2750	6.0000	15	5.4198	10.3624	13.1604	17.2273
4	6.2049	8.4798	13.8532	15.0654	16	5.7255	12.5935	17.4105	19.7638
5	7.1383	9.3982	14.2220	17.8307	17	6.7039	10.5788	15.6652	14.7749
6	5.2980	6.4679	14.0777	16.4710	18	7.4962	6.1530	14.6788	16.3473
7	10.2929	6.5933	16.0636	7.9346	19	10.2468	9.3473	19.4599	19.4101
8	9.2217	6.2664	17.0897	18.9597	20	6.6561	7.3969	15.2337	15.5027
9	5.3380	7.0400	14.6781	16.9644	21	8.8492	11.6157	28.1759	11.5218
10	5.4986	8.2008	16.7832	11.2568	22	6.3709	8.0318	14.0211	13.6095
11	6.3897	8.5479	20.7315	19.3512	23	11.8958	9.1135	12.8050	17.3681
12	5.0302	11.2354	12.9111	11.6199	24	8.9620	6.0161	20.6426	18.9328

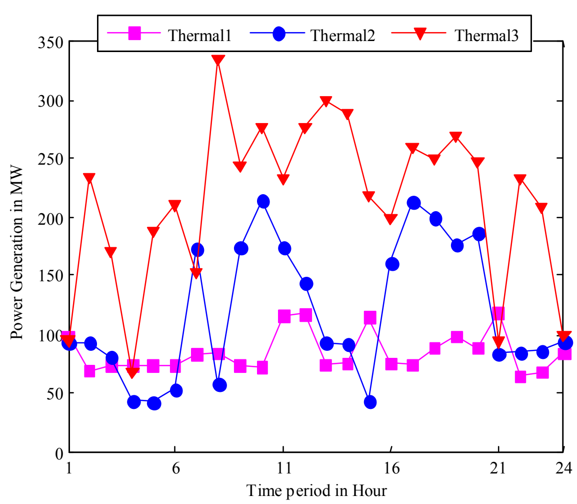

Fig. 2: Hourly optimal thermal plant generation obtained by ABC for CEES

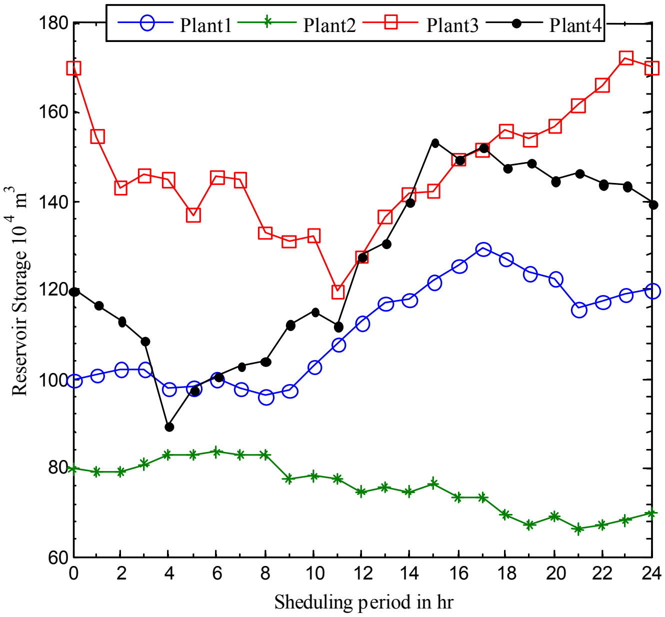

Fig. 3: Hourly hydro plant water storage trajectories obtained by ABC for CEES

Table 3: Comparison of optimal FC and ER concerning ABC with other methods

Methods	FC ($)	ER (lb)
DE	44913.51	19614.88
MODE	49677.15	22615.31
PSO	43334.38	18117.09
SOHPSO_TVAC	43045.33	17002.94
SA-MOCDE	43165.12	17464.35
IGSA	43299.75	17868.69
DCPSO	42118.58	16526.95
HCRO	42801.64	17623.01
IMOGSA	44492.37	17354.44
SDE	41697.23	17981.40
ABC	42809.87	16402.37

Competency with Other Method: Broadly, the strength of the ABC technique is examined in term of solution quality against other rivals. So, the best result was attained in CEES case have been compared in Table 3, As seen from the comparison, reported algorithms have tried to minimize FC in the desired values and pollutant ER into a tolerable value. Nevertheless, the ABC outperforms other contestant algorithm listed in the literature in the viewpoint of pollutant emission reduction and it is able to schedule the hydrothermal system with compromised minimum FC and agreeable ER in CEES case. Similarly, the proficiency of the ABC approach is compared pictorially in Figure 4, in which thirty compromised non-inferior solutions obtained by ABC, SA_MOCDE [8] IGAS [9] and IMOGSA [12] were diffused in the operational place. It is distinctly understood that the non-inferior solution obtained by ABC has a good variety, distribution and dominate those obtained by other three methods. Moreover, it brings out that ABC is better to optimize both objectives and efficient in solving short-term HTS problem.

Further, to confirm the capability of ABC on HTS, amount of savings in FC and reduction in ER have obtained against cited literatures was differentiated in Table 4, where the FC saved by ABC is $1403.64, $6867, $517.51, $165.46, $285.18, $489.88 and $982.5 while pollutant emission is 2442.51 (lb), 6142.94 (lb), 107.72 (lb), 600.57 (lb), 766.25 (lb) and 952.07 than DE [2] MODE [3] PSO [4] SOHPSO_TVAC [6] SA-MOCDE [8] IGSA [9] and IMOGSA [10] respectively. It is noticed that there are no significant savings in FC as compared with DCPSO [10] HCRO [11] and SDE [13] but there is praiseworthy pollutant emission reduction 117.58 (lb), 1143.64 (lb) and 879.03 (lb) respectively. If these three methods have tried to reduce the pollutant emission further the corresponding FC will be certainly greater than what the ABC algorithm has obtained.

Descriptive Statistics: The main intent of the descriptive statistic test is to compare the performance of the ABC algorithm with listed optimization algorithms for solving CEES problem. Therefore a descriptive statistical test was carried out using SPSS software with an optimized value of compromised FC and pollutant emission over the schedule horizon and the experimental results were

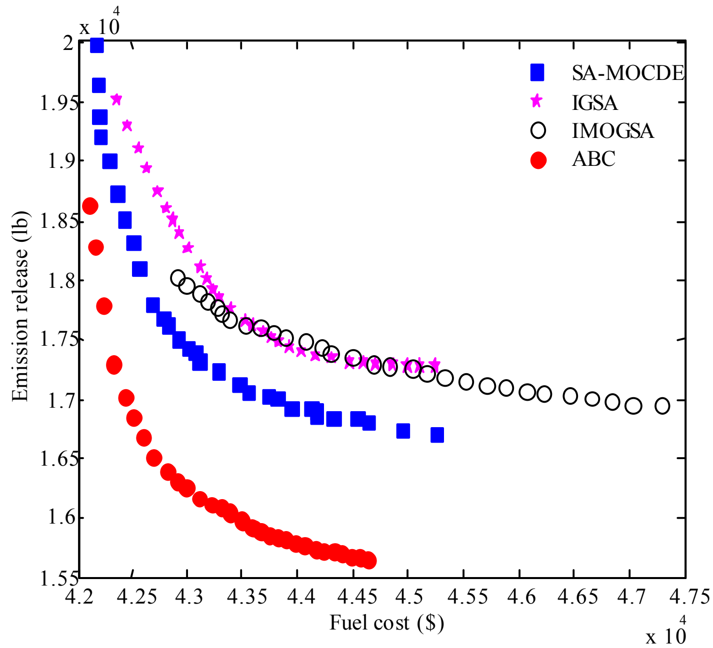

Fig. 4: The distribution of the non-inferior solutions of ABC and solutions of other methods

Table 4: Savings in FC and reduction in ER concerning ABC with respect to other methods

Methods	FC ($)	ER (lb)
DE	2103.64	3212.51
MODE	6867.28	6212.94
PSO	524.51	1714.72
SOHPSO_TVAC	235.46	600.57
SA-MOCDE	355.25	1061.98
IGSA	489.88	1466.32
DCPSO	---	124.58
HCRO	---	1220.64
IMOGSA	1682.5	952.07
SDE	---	1579.03

Table 5: Descriptive statistics for compromised FC over schedule horizon

	Fuel Cost in $					
Methods	Minimum	Maximum	Mean	Std. Deviation	Std Error	Rank
DE	1241.22	2468.56	1871.40	409.70	83.63	10
MODE	1296.82	2672.54	2069.88	393.23	80.27	8
PSO	871.34	2536.50	1805.60	432.66	88.32	11
SOHPSO_TVAC	1073.03	2351.36	1793.56	393.53	80.33	9
SA-MOCDE	1267.67	2335.05	1798.55	287.01	58.59	2
IGSA	1311.05	2102.25	1804.16	288.86	58.96	3
DCPSO	1120.79	2382.18	1754.94	345.41	70.51	6
HCRO	1238.23	2300.44	1783.40	348.03	71.04	7
IMOGSA	1290.50	2277.01	1853.86	315.40	64.38	4
SDE	1262.42	2232.61	1737.42	331.68	67.70	5
ABC	1089.81	2173.59	1783.75	280.10	57.18	1

Table 6: Descriptive statistics for compromised ER over schedule horizon

	Pollutant Emission (lb)					
Methods	Minimum	Maximum	Mean	Std. Deviation	Std Error	Rank
DE	187.90	1735.27	817.29	478.15	97.60	10
MODE	208.25	1870.97	942.31	508.68	103.83	11
PSO	181.17	1475.72	754.88	449.26	91.70	9
SOHPSO_TVAC	158.77	1345.94	708.46	386.98	78.99	8
SA-MOCDE	248.81	1351.76	727.68	302.36	61.72	3
IGSA	290.96	1032.12	744.53	295.33	60.28	2
DCPSO	160.69	1429.00	688.62	327.63	66.88	5
HCRO	194.19	1316.49	734.29	340.22	69.45	7
IMOGSA	257.11	1339.63	723.11	304.04	62.06	4
SDE	324.34	1345.60	749.23	333.39	68.05	6
ABC	250.74	1039.14	683.43	288.84	58.96	1

Table 7: Model summary of one way ANOVA for compromised FC over schedule horizon

ANOVA with F Test						
Attributes		Sum of Squares	df	Mean Square	F	Sig.
	Between People	2.529E7	23	1099544.454	7.541	.000
Within People	Between Items	1954355.380	10	195435.538		
	Residual	5961068.799	230	25917.690		
	Total	7915424.179	240	32980.934		
	Total	3.320E7	263	126254.550		
Grand Mean = 1823.3180						

Table 8: Model summary of one way ANOVA for compromised ER over schedule horizon

ANOVA with F Test						
Attributes		Sum of Squares	df	Mean Square	F	Sig
	Between People	2.871E7	23	1248266.084	4.543	.000
Within People	Between Items	1269685.593	10	126968.559		
	Residual	6427447.220	230	27945.423		
	Total	7697132.814	240	32071.387		
	Total	3.641E7	263	138430.619		
Grand Mean = 752.1657						

presented in Tables 5 and 6 respectively. Furthermore, the ranking of each optimization was tabulated according to standard deviation to help provide a clear picture of the consensus reached by the optimization technique. As the ABC algorithm has the lowest standard deviation, it is ranked first. Additionally, the smallest standard error suggests that most sample means are similar to the population mean and so the sample is likely to be an accurate reflection of the population.

Parametric Statistic Test: The SPSS software offers a parametric statistic test to study the significant difference between the results of FC and pollutant emission was obtained by the listed optimization methods. The statistics ANOVA summary table was obtained and the subsequent predictions are shown in the Tables 7 and 8 respectively. Here, the "sig." value is compared with alpha (Which is usually. 05, as known from literature). The decision rule is that the significance value (p) is less than alpha, the null hypothesis should be rejected otherwise the null hypothesis should not be rejected. In this case as p (.000) < alpha (0.05) the null hypothesis should be rejected and there was a significant difference between the groups as $F(10, 230) = 7.541$, $p=.000$ for FC and $F(10, 230) = 4.543$, $p=.000$ for pollutant emission over the schedule horizon.

Nonparametric Statistic Test: The Wilcoxon signed rank test is a nonparametric statistic analysis that has performed using SPSS to show significant statistical differences among the compromised FC and pollutant emission was obtained by ABC and other contestant

Table 9: Wilcoxon signed rank test statistics for compromised FC over the schedule horizon

	Sum of the ranks		Sig.		Sum of the ranks		Sig.
Pairwise Comparison	R^+	R^-	p-value	Pairwise Comparison	R^+	R^-	p-value
ABC- DE	298	2	.000	ABC- IGSA	297	3	.000
ABC- MODE	298	2	.000	ABC- DCPSO	261	39	.001
ABC- PSO	284	16	.000	ABC- HCRO	297	3	.000
ABC- SOHPSO_TVAC	297	3	.000	ABC-IMOGSA	300	0	.000
ABC- SA-MOCDE	300	0	.000	ABC-SDE	299	1	.000

Table 10: Wilcoxon signed rank test statistics for compromised ER over the schedule horizon

	Sum of the ranks		Sig.		Sum of the ranks		Sig.
Pairwise Comparison	R^+	R^-	p-value	Pairwise Comparison	R^+	R^-	p-value
ABC- DE	296	4	.000	ABC- IGSA	296	4	.000
ABC- MODE	297	3	.000	ABC- DCPSO	262	38	.0005
ABC- PSO	274	26	.000	ABC- HCRO	297	3	.000
ABC- SOHPSO_TVAC	297	3	.000	ABC-IMOGSA	300	0	.000
ABC- SA-MOCDE	298	2	.000	ABC-SDE	297	3	.000

algorithms. The experimental results were presented in the Tables 9 and 10, it shows the R^+, R^- and p-values computed for all the pairwise comparisons concerning ABC. In order to draw inferences about the tabulated results two hypotheses, the null hypothesis H_0 and the alternative hypothesis H_1, are defined. The null hypothesis is a statement of no significant difference between algorithms, whereas the alternative hypothesis represents the presence of a significant difference between algorithms. From the tables, it can be stated that the p values are.000 at the significance level $\alpha = 0.05$. The $p < 0.05$ is the stronger evidence to reject null hypothesis H_0 which means that the ABC shows a significant improvement to minimize FC and reduction in pollutant emission over DE [2] MODE [3] PSO [4] SOHPSO_TVAC [6] SA-MOCDE [8] IGSA [9] DCPSO [10] HCRO [11] IMOGSA [12] SDE [13].

CONCLUSION

In this paper at first the conflict objectives of such FC and pollutant ER are optimized simultaneously using ABC algorithm and the implication of normalized price penalty factor approach was exerted trade-off between them.

Second a statistical test using SPSS software is conducted with the simulated results of the proposed and previous methods over a scheduled horizon. The descriptive statistic test has ranked the ABC algorithm in first for solving HTS problem, whereas one-way ANOVA test was proved that the ABC has a significant difference between the groups and Wilcoxon signed rank test has confirmed its solution quality. Thus, it is inferred that the ABC algorithm can be a robust and cost-effective alternative for hydrothermal energy management considering emission aspects.

Nomenclature:

F, E	:	Total fuel cost ($) and emission release (lb)
T	:	Scheduling period in hour
t	:	Sub-interval
k, m	:	Index number
N_s	:	Number of thermal units
N_h	:	Number of hydro units
$P_{sit}, P_{hj,t}$	:	Generation of i^{th} thermal unit in t^{th} sub-interval
$P_{hj,t}$	:	Generation of j^{th} hydro unit in t^{th} sub-interval
$P_{si}^{\min}, P_{si}^{\max}$	:	Minimum and maximum generation limit of i^{th} thermal unit
$P_{hj}^{\min}, P_{hj}^{\max}$	:	Minimum and maximum generation limit of j^{th} hydro unit
a_{si}, b_{si}, c_{si}	:	Coefficients of the fuel cost curve of i^{th} thermal unit

e_{si}, f_{si}	:	Valve point effect coefficient of i^{th} thermal unit
α_{si}, β_{si}, γ_{si}, η_{si}, δ_{si}	:	Emission curve coefficients of i^{th} thermal plant
$P_{D,t}$	:	Total power demand in the t^{th} interval
$P_{L,t}$	:	Total network loss in the t^{th} interval
B_{ij}, B_{oi}, B_{oo}	:	Loss coefficient
$P_{i,t}$, $P_{j,t}$	:	Power generation of the i^{th} and j^{th} index of plants in the hybrid hydrothermal system.
C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j}, C_{6j},	:	Power generation coefficient of j^{th} hydro unit
$V_{hj,t}$	:	Storage volume of j^{th} reservoir at time t
$Q_{hj,t}$	:	Water discharge rate of j^{th} reservoir at time t
$V_h(j)^{begin}$ $V_h\,(j)^{end}$	:	Initial and final reservoir volumes
I_h	:	Natural inflow of j^{th} hydro reservoir at time t
R_u	:	Number of upstream plants
τ	:	Water transport time delay to immediate downstream plant in hours
$Q_{hj}^{\min}$, $Q_{hj}^{\max}$,	:	Minimum and maximum water discharge rate of j^{th} reservoir
$V_{hj}^{\min}$, $V_{hj}^{\max}$,	:	Minimum and maximum storage volume of j^{th} reservoir
$x_{hj}^{\min}$, $x_{hj}^{\max}$,	:	Lower and upper ranges of k^{th} food source in dimension l
$\phi_{k,l}$	:	Uniform random number between [-1, 1]
$x_{m,l}$	:	Randomly selected food source in dimension l
rand	:	Random number between [0, 1]

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