Solutions for Hydrothermal Systems Considering Cascaded Hydropower Plants

Phu Trieu Ha, Thuan Thanh Nguyen, Thang Trung Nguyen, and Dieu Ngoc Vo*

Abstract— *This paper proposes an improved cuckoo search algorithm (ICSA) for optimizing the operation of thermal power plants and hydrothermal power plants in a cascaded system. The major purpose of the problem is to reduce the total electricity generation cost of thermal power plants thank the most appropriate water discharge from hydropower plants in the cascaded system. The proposed ICSA method together with its original method, cuckoo search algorithm (CCSA) and another modified version, modified cuckoo search algorithm (MCSA) are implemented for two systems in which the second system considers valve effects on thermal units during the operation process. Different settings to iterations are tried to survey the improvement of ICSA over CSA and MCSA, and results are also compared to other existing methods. The proposed method can reach a lower cost but its search procedure is faster for the two systems. Consequently, ICSA is a powerful method for the optimal operation of the hydrothermal systems with cascaded reservoirs.*

Keywords— **Cuckoo search algorithm, cascaded hydropower plants, thermal power plants, hydrothermal system.**

1. INTRODUCTION

Nowadays, many hydropower plants are built in the same rivers where operation mode of upstream plants influence power energy of downstream plants significantly. In fact, inflow into upstream plants is from nature river and the flow is not influenced by electricity generation action of any companies or plants; however, inflow into downstream plants is dependened by upstream plants' water discharge via turbines or flood discharge. The operation of the hydropower plants is also a major contribution to the reduction of electricit generation cost from thermal power plants. The problem has a major meaning on power system. As considering high cost from thermal power plant and very low cost from hydropower plant, the purpose of the hydrothermal system is to reduce the cost of thermal power plants and satisfy all hydraulic constraints from reservoir of hydropower plants.

In recent decades, many researchers concerned the reduction of cost from thermal power plants in hydrothermal power system and applied optimzation tools for the problem. These methods are Two-phase neural network (TPNN) [1], Cultural algorithm (CA) [2], Real coded genetic algorithm (RCGA) [3], Binary coded genetic algorithm (BCGA) [3], Cuckoo search algorithm (CSA) [4], Chaotic hybrid differential evolution (CHDE) [5], Hybrid differential evolution and sequential quadratic programming (HDE–SQP) [6], Honey-bee Mating Optimization Algorithm (HBMOA) [7], Biogeography-Based Optimization (BBO) [8], Differential real-coded quantum-inspired evolutionary algorithm (DRQEA) [9], Gravitational Search Algorithm (GSA) [10], Improved self-adaptive PSO (ISPSO) [11], Mixed-binary evolutionary particle swarm optimizer (MB-EPSO) [12], Teaching learning based optimization (TLBO) [13], Quasi-oppositional teaching learning based optimization (QOTLBO) [13], Adaptive Chaotic Real Coded Genetic Algorithm (ACRCGA) [14], Improved differential evolution (IDE) [15], Quadratic Migration of Biogeography based Optimization (QMBBO) [16], Real coded chemical reaction based optimization (RCCRO) [17], Modified chaotic differential evolution algorithm (MCDEA) [18], and Modified dynamic neighborhood learning based particle swarm optimization (MDNLPSO) [19]. In Ref. [1], a two-phase neural network-based method was developed for dealing with the problem and compared to the standard augmented Lagrange method (ALM). Comparison of fuel cost has led to a conclusion that TPNN could obtain higher quality solution than ALM; however, there has not been evidence to conclude if TPNN could be faster for convergence than ALM once the information of tolerance and the number of iterations has not been reported. In addition, there has not been any conclusion of the performance of TPNN compared to other applied methods in the study. In Ref. [3], binary coded genetic algorithm (BCGA) and real coded genetic algorithm (RCGA) have been successfully applied. Comparison of yielded results has shown the superiority of RCGA over BCGA in terms of quality of solution for two systems; however, the two algorithms have not been compared to other applied methods and there have not been any conclusions of the performance of the better

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one, RCGA with other ones. An adaptive chaotic real coded genetic algorithm (ACRCGA) has been proposed to solve short-term hydrothermal scheduling (SHS) problem [14]. Crossover and mutation have been adaptive to improve the global search ability while the chaotic search and the RCGA have been combined to exploit the local search ability. The reported results including fuel cost and execution time have indicated that ACRCGA has been superior to RCGA and BCGA, and other ones; however, the verify of optimal solutions have pointed out that ACRCGA has violated the end volume constraint at reservoirs 3 and 4 and its optimal solution has been invalid to compare performance with others. It has been stated in [5] that Differential evolution (CDE) has coped with the difficulty of setting control parameter because mutation factor and crossover factor have been set to large range. Therefore, Chaotic hybrid differential evolution (CHDE) has been proposed by using chaos theory to set self-adaptive parameters automatically. Due to the improvement, the CHDE could reduce a huge number of trials for selecting the values for the two control parameters. Despite the advantage, the CHDE has not shown its potential persuasively when only one small system has been run to implement the proposed method. 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 [6]. In the method, the DE has played a main role to search solution meanwhile the SQP has enabled the search process closed to the global optimal solution or near global optimum. Several study cases were performed to test the efficiency of the method considering nonconvex objective and prohibited zone of hydro units. Ref. [15] has used Gaussian distribution for improved DE (IDE) method in aim to reduce a large number of trials for mutation factor and to improve the local search for CDE. The improvement of the IDE has been verified via testing on two systems with valve point loading effects. In [4], the result comparisons have indicated the CSA has outperformed GA, PSO, DE and TLBO; however, the study have also reported invalid solutions. Modified chaotic differential evolution algorithm (MCDEA) [18] has been developed by integrating an adaptive dynamic control mechanism for crossover factor and chaotic local search operation to avoid premature convergence effectively. Compared to other versions of DE, the MHDE was the best version obtaining the high solution quality and fast computational time. A novel teaching learning-based optimization (TLBO) [13] was mainly based on teaching phase and learning phase, and did not need any algorithm determining the control parameters. A combination of Modified dynamic neighborhood learning and particle swarm optimization (MDNLPSO) has been proposed in [19]. In the MDNLPSO, all particles were integrated into one group of neighborhoods and each individual one learnt experience from any another one available in the group. The method has been tested on three systems and the obtained results compared to other methods such as TLBO, QOTLBO, ALM and TPNN have revealed that the method was capable of searching high quality solution.

In this paper, Cuckoo search algorithm (CSA) [20], its modified version (MCSA) [21] and the proposed ICSA method are employed to find the most appropriate solutions for two hydrothermal systems. The results are also compared to other methods for concluding the real performance of CSA, MCSA and ICSA methods. In summary, the contributions of the paper are as follows:

1) Survey the real performance of CSA, MCSA and ICSA for two systems in order to show the best method for the hydrothermal systems.

2) Point out a strong method for hydrothermal systems and recommend its use for other problem in power system.

3) Find solutions with high quality resulting in low electricity cost for thermal power plants

4) Introduce a high-performance method with simple application

2. PROBLEM FORMULATION

The problem considers N_{tp} thermal power plants and N_{hp} hydropower in a hydrothermal system supplying electricity to loads. The period of time for optimizing the system is 24 hours and divided into 24 intervals in which each interval is one hour. So, the purpose is to reduce total electricity generation cost (*EGC*) as shown in the following model:

$$\text{Minimize } EGC = \sum_{t=1}^{T}\sum_{tp=1}^{N_{tp}} F_{tp,t} \tag{1}$$

where $F_{tp,t}$ is the electricity generation cost of the tp^{th} thermal power plant at the t^{th} considered interval.

$$F_{tp,t} = \left[a_{1,tp} + a_{2,tp}P_{tp,t} + a_{3,tp}P_{tp,t}^2 + \left| a_{4,tp} \times \sin\left(a_{5,tp} \times \left(P_{tp}^{\min} - P_{tp,t} \right) \right) \right| \right] \tag{2}$$

In addition, all following constraints must be exactly met.

- *Constraint of power balance***:** Total power of all hydropower plants, total power of all thermal power plants, power loss and load power must satisfy the following constraint:

$$\sum_{i=1}^{N_{tp}} P_{tp,t} + \sum_{j=1}^{N_{hp}} P_{j,t} - \Delta P_t - P_{Load,t} = 0 \tag{3}$$

where ΔP_t and $P_{Load,t}$ are power loss and power of load at the t^{th} interval; $P_{j,t}$ is the power generated by the j^{th} hydropower plant at the *tth* interval and is calculated by:

$$P_{j,t} = b_{1,j}(V_{j,t})^2 + b_{2,j}(W_{j,t})^2 + b_{3,j}W_{j,t}V_{j,t} + b_{4,j}V_{j,t} + b_{5,j}W_{j,t} + b_{6,j} \tag{4}$$

where $b_{1,j}$, $b_{2,j}$, $b_{3,j}$, $b_{4,j}$, $b_{5,j}$, $b_{6,j}$ are the known coefficients.

- *Constraints of reservoir volume:* Reservoir volume at the beginning and the end of the scheduled process must follow the constraints below:

$$V_{j,0} = V_{j,start} \quad (5)$$

$$V_{j,T} = V_{j,end} \quad (6)$$

where $V_{j,0}$ and $V_{j,start}$ are the reservoir volume at the beginning of operation process; $V_{j,T}$ and $V_{j,end}$ are the reservoir volume at the end of the operation process. $V_{j,start}$ and $V_{j,end}$ are predetermined factors while $V_{j,0}$ and $V_{j,T}$ are operation factors, which must be equal to $V_{j,start}$ and $V_{j,end}$, respectively.

- *Balance of water in reservoirs:* Reservoir volume, inflow and water discharge of considered reservoir and upstream reservoir must satisfy the following constraint.

$$V_{j,t-1} - V_{j,t} + Inf_{j,t} - W_{j,t} + \sum_{i=1}^{NoU} \sum_{t=1}^{T} (W_{i,t-\tau_{i,j}}) = 0 \quad (7)$$

where $V_{j,t}$ *and* $Inf_{j,t}$ are reservoir volume and water inflow of the *jth* hydropower plant at the *tth* interval. $\tau_{i,j}$ is the traveling time of water from the *ith* upstream reservoir to the *jth* downstream reservoir*; NoU* is the number of upstream reservoir of the *jth* considered reservoir.

- *Reservoir and discharge limits:* Two main operation factors of hydropower plants are volume of reservoir and discharge via turbines. The constraints of the two factors can guarantee safety for reservoir and turbines. The constraints are follows:

$$V_j^{\min} \le V_{j,t} \le V_j^{\max};\ j = 1, ..., N_{hp}; t = 1, ..., T \quad (8)$$

$$W_j^{\min} \le W_{j,t} \le W_j^{\max};\ j = 1, ..., N_{hp}; t = 1, ..., T \quad (9)$$

where $V_j^{\min}$ and $V_j^{\max}$ are the lower limit and upper limit of the j^{th} reservoir, respectively; $W_j^{\min}$ and $W_j^{\max}$ are the lower limit and upper limit of water discharge of the j^{th} reservoir, respectively.

- *Constraint of generated power:* Generator of hydropower plants and thermal power plants must operate within lower and upper generation as follows:

$$P_j^{\min} \le P_{j,t} \le P_j^{\max} \quad (10)$$

$$P_{tp}^{\min} \le P_{tp,t} \le P_{tp}^{\max} \quad (11)$$

where $P_{tp}^{\min}$ and $P_{tp}^{\max}$, and $P_j^{\min}$ and $P_j^{\max}$ are the lowest and highest power of the tp^{th} thermal power plant and the j^{th} hydropower plant.

3. THE PROPOSED METHOD

3.1. Lévy flight technique of CCSA

Lévy flights technique is applied for producing new solutions as the following equation:

$$S_k = S_k + \alpha\left(S_k - S_{best}\right) \oplus Levy(\beta) \quad (12)$$

where α is positive factor, which can be selected higher than 0 and less than 1; S_{best} is the best solution of the current solutions; and *Levy(β)* is Lévy distribution [20].

3.2 Mutation operation of CCSA

Similar to DE, CSA also uses mutation technique as follows:

$$S_k = \begin{cases} S_k + r_1.(S_1 - S_2) \ \ if \ \ r_2 < MF \\ S_k \qquad\qquad otherwise \end{cases} \quad (13)$$

where *MF* is mutation parameter which can be selected between 0 and 1; r_1 and r_2 are random numbers within 0 and 1; S_1 and S_2 are randomly selected solutions from the whole solutions.

3.3 The proposed mutation technique

The proposed ICSA method still applies Lévy flight technique of CCSA but mutation technique is proposed to be modified by applying the following steps:

$$\Delta F_k = \frac{F\left(S_k\right)}{F\left(S_{best}\right)} \quad (14)$$

$$\Delta F_{mean} = \frac{\sum_{k=1}^{NoP} F\left(S_k\right)}{F\left(S_{best}\right)} \quad (15)$$

where *NoP* is population; $F(S_k)$ and $F(S_{best})$ are fitness function of the kth solution and the best solution.

The mutation technique is modified and performed by using the following equation (16):

$$S_k = \begin{cases} S_k + r_1.(S_1 - S_2) & if \ \left(r_2 < MF\right) \& \left(\Delta F_k > \Delta F_{mean}\right) \\ S_k + r_1.\begin{pmatrix} S_1 - S_2 \\ +S_3 - S_4 \end{pmatrix} & if \ \left(r_2 < MF\right) \& \left(\Delta F_k \le \Delta F_{mean}\right) \& \left(S_k \ne S_{best}\right) \\ S_{best} + r_1.\begin{pmatrix} S_1 - S_2 + S_3 - S_4 \\ +S_5 - S_6 \end{pmatrix} & if \ S_k = S_{best} \\ S_k & if \ \left(r_2 \ge MF\right) \end{cases} \quad (16)$$

where S_1, S_2, S_3, S_4, S_5 and S_6 are randomly selected solutions from the current solutions.

4. THE APPLICATION OF THE PROPOSED METHOD FOR THE PROBLEM

4.1 Initialization and constraint handling method

Each solution is represented by S_k= [$P_{tp,t,k}$, $W_{j,t,,k}$], where tp = 2, …, N_{tp} and t=1, …, T for $P_{tp,t,k}$ and j=1, …, N_{hp} and t=1, …, T-1 for $W_{j,t,k}$. In addition, $P_{tp,t,k}$, $W_{j,t,,k}$ must satisfy constraints shown in formulas (9) and (10). As a result, reservoir volume of the j^{th} hydropower plant at the t^{th} interval can be reached by:

$$V_{j,t} = V_{j,t-1} + Inf_{j,t} - W_{j,t} + \sum_{i=1}^{NoU}(W_{i,t-\tau_{i,j}});\ t = 1, \ldots, T-1 \tag{17}$$

where $V_{j,0}$ and $V_{j,T}$ are obtained by using equations (5) and (6), respectively.

As a result $W_{j,T,,k}$ can be obtained by:

$$W_{j,T,k} = V_{j,0} - V_{j,T} - \sum_{t=1}^{T-1} W_{j,t,k} + \sum_{t=1}^{T} Inf_{j,t} + \sum_{i=1}^{NoU}\sum_{t=1}^{T}(W_{i,t-\tau_{i,j},k}) \tag{18}$$

Power output of hydropower plants can be calculated by using equation (4) and power output of the first thermal power plant $P_{1,t,k}$ is obtained by using equation (3). As a result, fitness function of the kth solution is evaluated by calculate $F(S_k)$ in the following equation:

$$F(S_k) = \left(\sum_{t=1}^{T}\sum_{tp=1}^{N_{tp}} F(P_{tp,t,k}) + \varphi_1 \sum_{t=1}^{T} (\Delta P_{1,t,k})^2 + \varphi_2 \sum_{j=1}^{N_{hp}}\sum_{t=1}^{T-1} (\Delta V_{j,t,k})^2 + \varphi_3 \sum_{j=1}^{N_{hp}} \left(\Delta W_{j,T,k}\right)^2 \right) \tag{19}$$

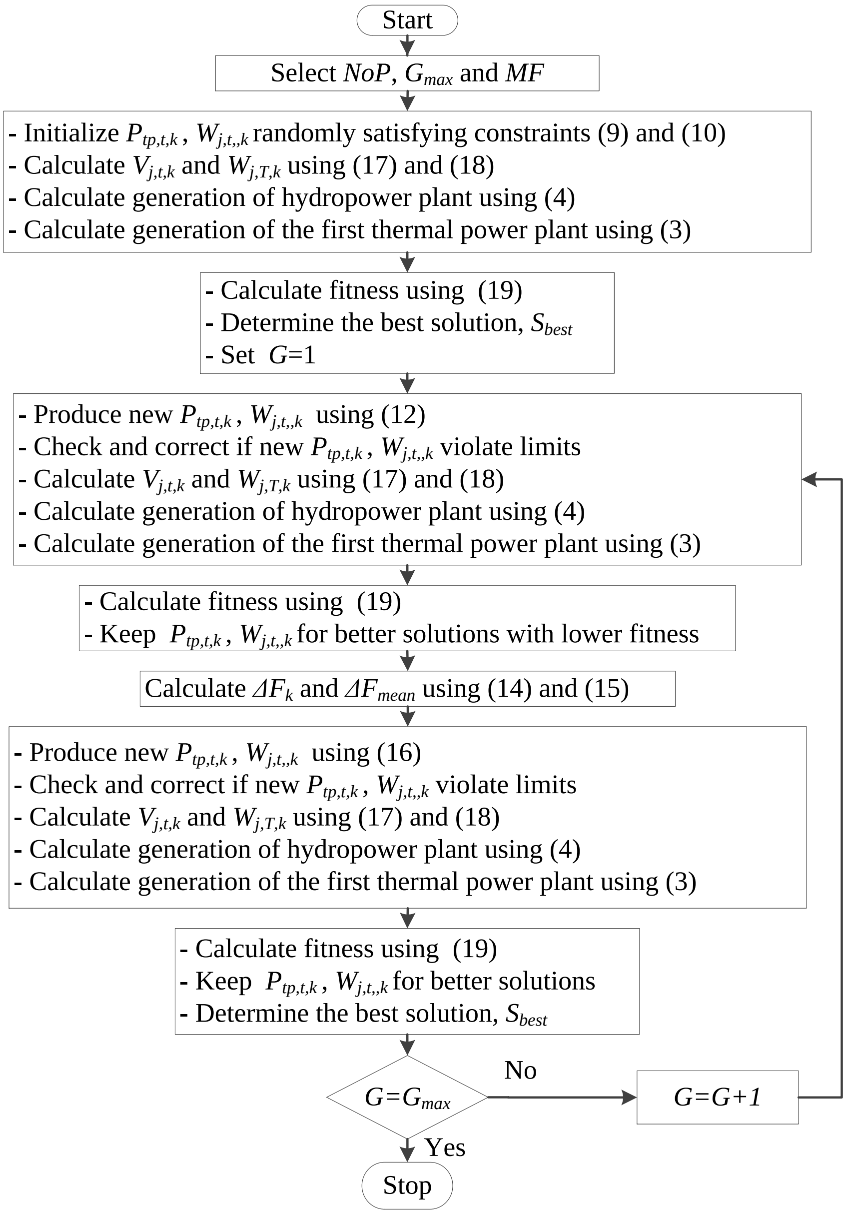

Fig. 1. The flowchart of using ICSA for solving the considered problem.

where φ_1, φ_2 and φ_3 are factors for the violations of power output of the first thermal power plant, the violation of reservoir volume and the violation of water discharge; $\Delta P_{1,t,k}$, $\Delta V_{j,t,k}$, $\Delta W_{j,t,k}$ are the violation of power output of the first thermal power plant, the violation of reservoir volume and the violation of water discharge at the *Tth* interval, respectively.

4.2 The whole search process of the proposed ICSA

The overall procedure of the proposed ICSA for optimizing operation of the hydrothermal system is shown in Figure 1.

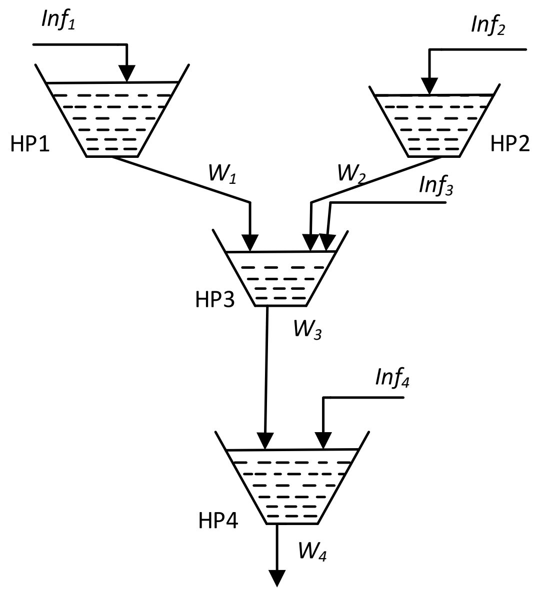

Fig. 2. The cascaded hydropower plants configuration in two considered systems.

5. NUMERICAL RESULTS AND DISCUSSIONS

5.1 Result obtained by three CSA methods

In this paper, we have considered two systems with the same number of hydropower plants and the same number of thermal power plant consisting of four cascaded hydropower plants and one thermal power plant. However, valve effects on thermal units have been only considered in system 2. The four cascaded hydropower plants in the two systems has the same configuration as shown in Figure 2. In the figure, hydropower plant 1 (HP1) and hydropower plant 2 (HP2) are two upstream plants of hydropower plant 3 (HP3) whereas HP3 is the upstream plant of hydropower plant 4 (HP4) and HP4 is the downstream plant. The determination is accomplished by using the directions of the inflows and discharge between two nearby hydropower plants. As indicated from the figure, inflows into HP1 and HP2 are only natural inflows, which are, respectively, Inf_1 and Inf_2 whereas there are two inflows into HP3 and HP4 consisting of natural inflow and discharge from upstream reservoir. In fact, HP3 has one natural inflow Inf_3 and two discharges from HP1 and HP2, W_1 and W_2 meanwhile R4 has one natural inflow Inf_4 and one discharge from HP3, W_3. Data of the two systems are respectively taken from [1] and [3]. For implementation of the three CSA methods, population size *NoP* and the maximum iteration G_{max} are respectively set to 200 and 3,000 meanwhile the mutation factor is set to ten values from 0.1 to 1.0. The three methods are run on Matlab 2016b and personal computer with i7-2.0 Ghz processor and 4 Gb of ram. For each study case, 50 trial runs are executed for each method.

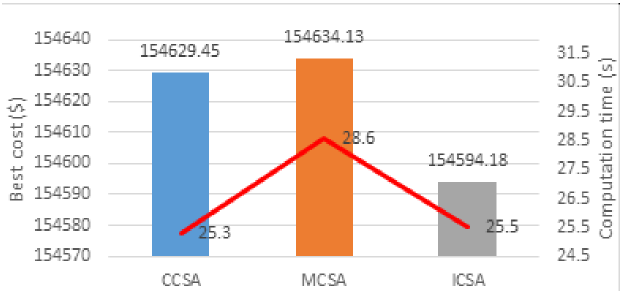

Fig. 3. The best cost and computation time from three methods for system 1.

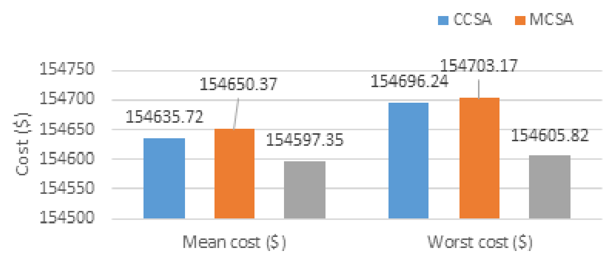

Fig. 4. The worst cost and mean cost from three methods for system 1.

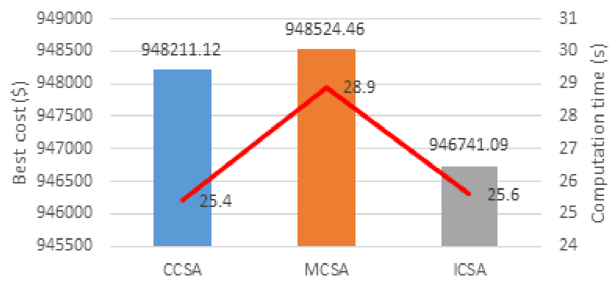

Fig. 5. The best cost and computation time from three methods for system 2.

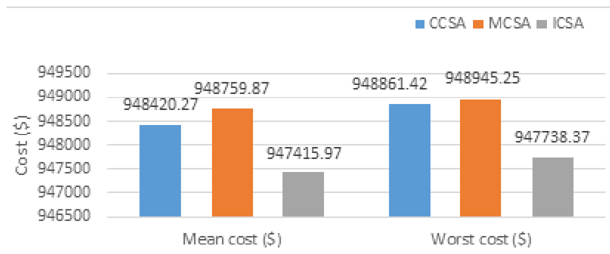

Fig. 6. The worst cost and mean cost from three methods for system 2.

Table 1. Saving cost and improvement percentage of ICSA as compared to CCSA and MCSA

System	Method	Best cost		Mean cost		Worst cost	
		Saving cost ($)	IP (%)	Saving cost ($)	IP (%)	Saving cost ($)	IP (%)
1	CSA	35.28	0.02	41.54	0.03	102.06	0.07
	MCSA	39.95	0.03	56.19	0.04	108.99	0.07
2	CSA	1470.04	0.16	1679.18	0.18	2120.33	0.22
	MCSA	1783.37	0.19	2018.78	0.21	2204.16	0.23

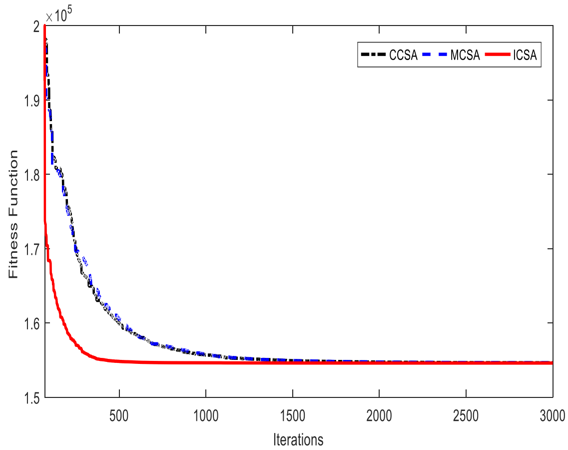

Fig. 7. Fitness convergence characteristics for system 1 without valve-point loading effects.

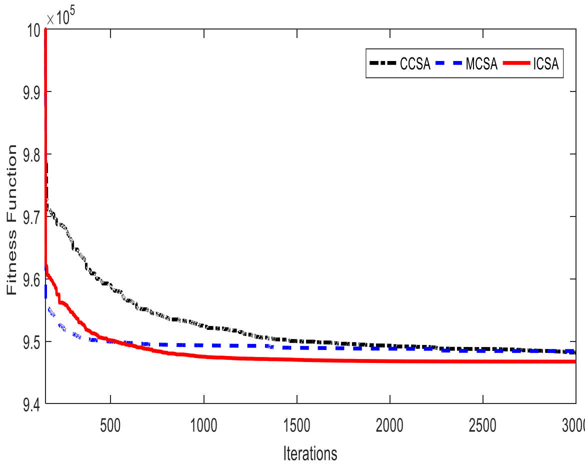

Fig. 8. Fitness convergence characteristics for system 2 with valve-point loading effects.

The summaries of obtained results from the CSA methods for the two systems are given in Figure 3 and Figure 4 for system 1 and Figure 5 and Figure 6 for system 2. The best minimum costs for CCSA, MCSA and ICSA are respectively $154629.454, $154634.128 and $154594.1766 for system 1, and $948211.1229, $948524.4587 and $946741.0872 for system 2. Clearly, ICSA has obtained the best optimal solutions among the three methods due to its lowest minimum cost. Similarly, ICSA has reached better mean cost and worst cost than CCSA and MCSA for the two systems. For better understanding of the real performance of ICSA, saving cost and improvement percentage of the best cost, mean cost and worst cost are reported in Table 1. As compared to CCSA and MCSA, the proposed ICSA method could reduce the best cost by $35.28 and $39.95 for system 1 and $1470.04 and $1783.37 for system 2. The saving cost is corresponding to the improvement percent of 0.02% and 0.03% for system 1 and 0.16% and 0.19% for system 2. The comparison of the mean cost and worst cost is approximately similar or better since the proposed method could reach IP up to 0.21% for mean cost and 0.23% for the worst cost. Clearly, the proposed ICSA is more effective than CCSA and MCSA. In terms of execution time comparison, MCSA has revealed its weak point since it reports the longest time for both systems whereas CCSA and ICSA have shown competitive figures. In fact, CCSA and ICSA methods have used the approximate simulation time for these systems; however, ICSA is much faster in finding the promising solutions for these systems. The convergence characteristics for the systems depicted in Figure 7 and Figure 8 have illustrated the different convergence figures obtained by the three methods. The ICSA has reached more effective solution than two others and the value is much less than that of CCSA and is extremely less than that of MCSA.

5.2 Survey of real performance of the propose method

In order to investigate the real performance of the proposed ICSA, we have run it together with CCSA and MCSA for the two systems with different settings for G_{max} whereas population size is still 200. Figure 9 and Figure 10 indicate that the best cost of the proposed ICSA at G_{max}=3,000 is still less than that of CCSA and MCSA at G_{max}=3,000, G_{max}=4,000 G_{max}=5,000. So, the proposed method is very fast to converge to the high quality solutions as compared to its original method and another modified version.

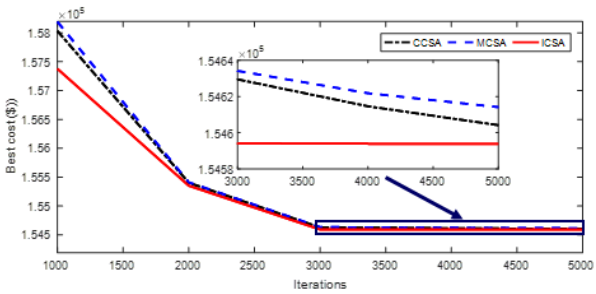

Fig. 9. Impact of iterations on the best cost of three methods for system 1.

Table 2. Comparison of results by ICSA and other methods for two systems

System 1			System 2		
Method	Best cost ($)	CPU (s)	Method	Best cost ($)	CPU (s)
TPNN [1]	154,808.5	-	BCGA [3]	952,618.00	66.3
ALM [1]	154,739	-	RCGA [3]	951,559.24	57.32
PSO [11]	154,705	-	DE [6]	947,497.85	-
ISAPSO [11]	154,594 .9	-	HDE–SQP [6]	945,293.81	-
BBO [8]	154,670.7707	63	ICSA	946,741.087	25.6
TLBO [13]	154,693.135	23.8			
ICSA	154594.1766	25.5			

Table 3. Optimal discharge and verification of volume obtained by the proposed method for system 2

t	Optimal discharge				Calculated reservoir volume			
	$W_{1,t}$ (10^4 m^3)	$W_{2,t}$ (10^4 m^3)	$W_{3,t}$ (10^4 m^3)	$W_{4,t}$ (10^4 m^3)	$V_{1,t}$ (10^4 m^3)	$V_{2,t}$ (10^4 m^3)	$V_{3,t}$ (10^4 m^3)	$V_{4,t}$ (10^4 m^3)
1	9.790293	6.803944	30	13.00012	100.209707	81.19606	148.1	109.7999
2	9.554395	6.02257	29.99896	13.00003	99.6553121	83.17349	126.301	99.19985
3	9.525171	6.967059	29.99879	13.0003	98.1301412	85.20643	110.0925	87.79954
4	10.93558	9.467846	16.95254	13.0009	94.1945639	84.73858	111.4983	74.79865
5	10.84217	9.437955	29.99976	13.00087	89.3523941	83.30063	100.0463	91.79777
6	9.882311	8.92085	15.23104	13.00043	86.4700826	81.37978	106.7179	108.7963
7	5.000306	6.001407	30	13.00086	89.4697768	81.37837	100.0279	125.7942
8	5.001968	6.000001	19.71246	13	93.4678083	82.37837	101.6357	129.7468
9	10.7583	10.14952	12.74089	15.10405	92.7095117	80.22885	103.816	144.6425
10	10.52177	9.401429	12.62226	14.04204	93.187744	79.82742	103.1971	145.8315
11	9.663723	10.07866	12.93224	16.00145	95.5240212	78.74875	108.0232	159.83
12	11.1345	11.77802	13.21157	19.56564	94.3895233	74.97073	117.4829	159.9768
13	9.391926	10.15016	14.66581	16.43761	95.9975969	72.82057	125.8822	156.2801
14	8.114572	7.854908	14.88693	14.81583	99.8830253	73.96567	135.2085	154.0866
15	5	6.000103	18.96984	13.00039	105.883025	76.96556	140.4086	154.0184
16	5.000972	6.027941	18.86394	13.00097	110.882053	78.93762	141.8094	154.229
17	5	6.003674	18.05553	13.00012	114.882053	79.93395	138.6088	155.8947
18	5.005276	6.000026	14.15238	13.00526	117.876777	79.93392	137.4575	157.7764
19	8.392325	9.311518	13.74613	16.81897	116.484451	77.62241	135.7393	159.9272
20	9.987449	12.79911	11.58146	19.96861	112.497002	72.8233	136.1668	158.8226
21	7.263148	10.11735	10.00766	18.02745	112.233854	71.70595	142.5514	158.8506
22	5	6.000234	10.00677	13.00402	115.233854	74.70571	153.8436	159.999
23	7.995821	10.35979	10.00002	22.50046	116.238033	72.34592	164.9059	151.2447
24	6.238033	10.34592	10.02323	22.82613	120	70	170	140

Table 4. Optimal discharge and verification of volume obtained by HDE-SQP for system 2

t	Optimal discharge				Calculated reservoir volume			
	$W_{1,t}$ (10^4 m^3)	$W_{2,t}$ (10^4 m^3)	$W_{3,t}$ (10^4 m^3)	$W_{4,t}$ (10^4 m^3)	$V_{1,t}$ (10^4 m^3)	$V_{2,t}$ (10^4 m^3)	$V_{3,t}$ (10^4 m^3)	$V_{4,t}$ (10^4 m^3)
1	15	14.1574	10.4286	25	95	73.8426	167.6714	97.8
2	9.6785	14.4767	10	25	94.3215	67.3659	165.8714	75.2
3	14.1664	14.721	14.7978	23.3689	88.1551	61.6449	170.0736	53.4311
4	12.3559	14.9439	10	25	82.7992	55.701	185.9095	28.4311
5	13.7043	15	13.0694	25	75.0949	48.701	204.4832	13.8597
6	15	15	15.1031	25	67.0949	40.701	220.457	-1.1403
7	12.7767	15	11.707	25	62.3182	31.701	240.3982	-11.3425
8	14.9233	14.9926	14.0539	25	56.3949	23.7084	258.3443	-26.3425
9	14.3332	14.9524	13.4896	25	52.0617	16.756	273.6314	-38.2731
10	15	14.0531	13.5601	25	48.0617	11.7029	290.9946	-48.17
11	12.8343	13.1616	14.6854	25	47.2274	7.5413	306.635	-61.463
12	15	14.8386	14.0709	25	42.2274	0.7027	324.5165	-72.4091
13	14.7932	14.9996	14.4336	25	38.4342	-6.2969	340.9703	-83.9195
14	14.6232	15	13.6017	25	35.811	-12.2969	358.5302	-95.3594
15	14.7549	14.9967	14.0762	25	32.0561	-18.2936	377.0858	-105.674
16	14.7232	15	14.3364	25	27.3329	-25.2936	394.3722	-116.603
17	14.6576	15	14.4626	24.9991	21.6753	-33.2936	411.6645	-127.169
18	14.5671	15	14.5195	24.9971	15.1082	-42.2936	428.8649	-138.564
19	14.7613	14.9997	14.6386	25	7.3469	-50.2933	444.8839	-149.488
20	13.9412	11.0033	13.2556	23.418	-0.5943	-53.2966	462.1954	-158.569
21	7.1437	11.7499	14.4881	23.5978	-0.738	-56.0465	479.4686	-167.705
22	13.6309	11.6679	17.8084	20.2347	-6.3689	-58.7144	492.6011	-173.42
23	14.7468	15	14.6791	24.9963	-12.1157	-65.7144	497.069	-183.778
24	14.9999	15	13.1333	25	-17.1156	-72.7144	509.3165	-195.522

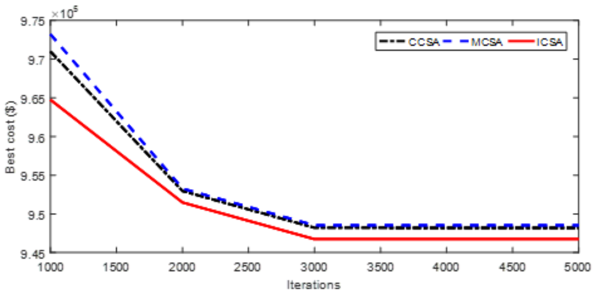

Fig. 10. Impact of iterations on the best cost of three methods for system 2.

5.3 Comparisons of results from the proposed method and others

The comparisons of the obtained results by CSA methods and other methods are reported in Table 2. The cost indicates that ICSA can reach lower electricity generation cost than approximately all methods for two systems excluding HDE–SQP for system 2 but HDE-SQP has reported violated solution. In order to show the violation of HDE-SQP for system 2, we have reported optimal discharge of the method and then reservoir volume at the end of each interval has been calculated for each hydropower plant. In addition, we have also reported the same data for the proposed method. Table 3 and Table 4 summarize the information of the proposed method and HDE-SQP, respectively. The reservoir volume at the 24th interval of reservoirs 1, 2, 3 and 4 shown in Table 3 is respectively 120, 70, 170 and 140 but that from HDE-SQP shown in Table 4 is -17.1156, -72.7144, 509.3165 and -195.522. Clearly, the values of the proposed method are the same as input data shown in [3] but the values from HDE-SQP are much different from the input data. The exact calculation shows ICSA could reach less cost than other methods from $0.72 to $214.32 for system 1 and $1447.28 to $5876.91 for system 2. The less cost indicates that ICSA can improve performance up to 0.14% for system 1 and 0.62% for system 2. Furthermore, the computation time (CPU) of the proposed method is equal or shorter than that of compared methods excluding some methods have not reported the value. Obviously, the proposed ICSA is a promising method for the two systems.

6. CONCLUSIONS

In this paper, the conventional cuckoo search algorithm, its modified version, and the proposed ICSA have been employed to find the optimal solutions for hydrothermal optimization operation problems. In the considered problem, not only the reservoir volume constraints but also the cascaded reservoirs are taken into account in addition to the non-convex fuel cost function of thermal units. Therefore, the complicated problem is a challenge to the CSA methods. Two hydrothermal systems are employed including one system ignoring and another considering valve point loading effects on thermal units. The numerical comparison indicated that the proposed ICSA method has obtained very high-quality solutions for all systems and it has been faster than most methods, which obtain feasible solutions. Consequently, the ICSA method is a promising optimization tool for the problem where cascaded reservoirs with complex hydraulic constraints are considered. Among the three applied CSA methods, the proposed ICSA is the strongest since it can obtain the lowest objective function with the lowest maximum number of iterations whereas MCSA is the worst method with the highest value of the objective function and the longest simulation time as well as the highest maximum number of iterations. In addition, surveys of the impact of iterations on results from the three methods indicate ICSA can be at least two times faster than CCSA and MCSA. So, it concludes that the proposed ICSA is one of the most effective methods for the problem with hydropower plants located in cascaded systems.

REFERENCES

[1] R. Naresh and J. Sharma, "Two-phase neural network based solution technique for short term hydrothermal scheduling," *IEEE Proc-Gener. Transm. Distrib,* vol. 146, no. 6, pp. 657-663, 1999.

[2] X. Yuan and Y. Yuan, "Application of cultural algorithm to generation scheduling of hydrothermal systems," *Energy Conversion and Management,* vol. 47, p. 2192–2201, 2006.

[3] S. Kumar and R. Naresh, "Efficient real coded genetic algorithm to solve the non-convex hydrothermal scheduling problem," *Int J Electr. Power Energy Syst,* vol. 29, no. 10, p. 738–47, 2007.

[4] H. Dubey, M. Pandit and B. Panigrahi, "Cuckoo Search Algorithm for Short Term Hydrothermal Scheduling," *Proceedings of ICPERES 2014, Lecture Notes in Electrical Engineering,* vol. 326, pp. 573-589, 2014.

[5] X. Yuan, B. Cao, B. Yang and Y. Yuan, "Hydrothermal scheduling using chaotic hybrid differential evolution," *Energy Conversion and Management,* vol. 49, p. 3627–3633, 2008.

[6] S. Sivasubramani and K. S. Swarup, "Hybrid DE–SQP algorithm for non-convex short term hydrothermal scheduling problem," *Energy Conversion and Management,* vol. 52, pp. 757-761, 2011.

[7] H. B. Tavakoli and B. Mozafari, "Short-term Hydrothermal Scheduling via Honey-bee Mating Optimization Algorithm," *Power and Energy Engineering Conference (APPEEC), Asia-Pacific,* pp. 1-5, 2012.

[8] M. Basu and S. Datta, "Biogeography-Based Optimization for Short-term Hydrothermal Scheduling," *Emerging Trends in Electrical Engineering and Energy Management (ICETEEEM), International Conference,* pp. 38-43, 2012.

[9] Y. Wang, J. Zhou, LiMo, R. Zhang and Y. Zhang, "Short-term hydrothermal generation scheduling using differential real-coded quantum-inspired evolutionary algorithm," *Energy,* vol. 44, pp. 657-671, 2012.

[10] A. K. Barisal, N. C. Sahu, R. C. Prusty and P. K. Hota, "Short-term hydrothermal scheduling using Gravitational Search Algorithm," *2nd International Conference on Power, Control and Embedded Systems,* pp. 1-6, 2012.

[11] Y. Wang, J. Zhou, C. Zhou, Y. Wang, H. Qin and Y. Lu, "An improved self-adaptive PSO technique for short-term hydrothermal scheduling," *Expert Systems with Applications,* vol. 39, pp. 2288-2295, 2012.

[12] V. H. Hinojosa and C. Leyton, "Short-term hydrothermal generation scheduling solved with a mixed-binary evolutionary particle swarm optimizer," *Electric Power Systems Research,* vol. 92, p. 162–170, 2012.

[13] P. K. Roy, A. Sur and D. K. Pradhan, "Optimal short-term hydro-thermal scheduling using quasi-oppositional teaching learning based optimization," *Engineering Applications of Artificial Intelligence,* vol. 26, p. 2516–2524, 2013.

[14] N. Fang, J. Zhou and J. Ma, "Short-term Hydrothermal Scheduling Based on Adaptive Chaotic Real Coded Genetic Algorithm," *IEEE conference on Intelligent Control and Automation,* pp. 3412-3416, 2014.

[15] M. Basu, "Improved differential evolution for short-term hydrothermal scheduling," *Electrical Power and Energy Systems,* vol. 58, p. 91–100, 2014.

[16] G. Kumar, V. Sharma, R. Naresh and P. K. Singhal, "Quadratic Migration of Biogeography based

Optimization for Short Term Hydrothermal Scheduling," *Networks & Soft Computing (ICNSC), First International Conference on*, pp. 400-405, 2014.

[17] K. Bhattacharjee, A. Bhattacharya and S. H. Dey, "Real coded chemical reaction based optimization for short-term hydrothermal scheduling," *Applied Soft Computing*, vol. 24, p. 962–976, 2014.

[18] J. Zhang, S. Lin and W. Qiu, "A modified chaotic differential evolution algorithm for short-term optimal hydrothermal scheduling," *Electrical Power and Energy Systems*, vol. 65, pp. 159-168, 2015.

[19] A. Rasoulzadeh-akhijahani and B. Mohammadi-ivatloo, "Short-term hydrothermal generation scheduling by a modified dynamic neighborhood learning based particle swarm optimization," *Electrical Power and Energy Systems*, vol. 67, p. 350–367, 2015.

[20] X. S. Yang, S. Deb. Cuckoo search via Lévy flights. *In: Proc. World congress on nature & biologically inspired computing (NaBIC 2009)*, India, pp. 210–214, 2009.

[21] S. Walton, O. Hassan, K. Morgan, M. R. Brown. Modified cuckoo search: A new gradient free optimisation algorithm. *Chaos, Solutions & Fractals*, Vol. 44, pp. 710–718, 2011.