Chapter

Dynamic Economic Load Dispatch of Hydrothermal System

Soudamini Behera, Ajit Kumar Barisal and Sasmita Behera

Abstract

A Quasi Oppositional Gray Wolf Optimization (QOGWO) algorithm has been used in this work to decipher the economic load dispatch of hydrothermal system. Dynamic economic load dispatch problem involves scheduling of committed generators to meet the load demand with minimum fuel cost and several constraints which are dynamic in nature. It is basically short-term hydrothermal scheduling (STHS) problems through cascaded reservoirs. Instead of pseudo-random numbers quasi-opposite numbers are used to initialize population in the proposed QOGWO method so that the convergence rate of GWO increases. The viability of the projected approach is verified in three standard multi-chain cascaded hydrothermal systems with four interconnected hydro systems. The load and number of thermal units differ from one system to another. Water transportation delay between interconnected reservoirs, Valve Point Loading (VPL) have been considered in different combination in three cases. The technique put forth with established superior to many recent findings for the STHS problems with increased complexities.

Keywords: hydrothermal scheduling, cascaded reservoir, gray wolf optimizer (GWO), quasi oppositional-based learning, STH problem, VPL effect

1. Introduction

Over the last few years, we are in a shortage of energy and facing the environmental pollution problem. So, now a day's wise utilization of energy and the operating cost minimization are major issues in the energy field. This signifies constraints of hydrothermal systems must be modified and more robust technique is required to provide more accurate scheduling results. The main aim of optimal HTS of an electrical system is to optimize hydrothermal generations so that the load demand is fulfilled in a scheduled time with accommodating several system constraints of the hydrothermal system. It is very complicated than that of the thermal system due to nonlinearity.

The Stochastic methods like Genetic Algorithm (GA) [1], Quick Evolutionary Programming (QEP) [2], Improved Particle Swarm Optimization (IPSO) [3], Teaching Learning Based Optimization (TLBO) TLBO [4], Symbiotic Organisms Search (SOS) [5], Intensified water cycle approach (IWCA) [6] have used for solving STH problems. GWO [7] is a simple, fast and effective global optimization method. GWO algorithm has been applied for the solution of non-convex and dynamic economic load dispatch problem (ELDP) of electric power system [8]. GWO has successfully solved various ELD problems [9]. Many researchers have demonstrated that an opposite candidate gives a more optimal solution than the candidate. Opposition Based Gray Wolf Optimizer (OGWO) has been implemented in solving ELD problem [10] for thermal power generators which increases the success rate and the convergence speed of GWO.

This study applies Quasi Opposition based GWO (QOGWO) for solving HTS problem of a hydrothermal system which prime objective is to allocate the hydro generation between the multi-reservoir cascaded units with PDZ and thermal units with VPL effect. The objective is to cut the total fuel cost of the thermal system with accommodating several limitations of the hydrothermal system which makes it a non-convex problem. To establish that the intended approach is better, a rigorous exercise of the QOGWO for a hydrothermal system, with the gradual increase of complexity and dimension, is considered in this study. In contrast to recent techniques, the outcomes of the QOGWO technique exhibits superiority for operating cost as well as the convergence characteristics to achieve the optimal result in all the cases tested here.

2. Formulation of STHS Problem

The STHS problem is to allocate the generation to the hydro and thermal units so that the required load demand is achieved and it reduces the net cost without affecting other constraints of Hydro and Thermal systems.

2.1 Hydro-thermal scheduling (HTS)

Since hydropower unit's fuel cost are trivial when assessed with that of thermal unit, the optimal HTS solution lessens the net coal cost of the thermal units with the maximum utilization of the accessible hydro resource. In line with this, the optimal HTS problem is formulated as the fuel cost *FC* as given in (1).

$$FC\left(PT_{i,j}\right) = \sum_{i=1}^{Ns}\sum_{j=1}^{Z} a_i PT_{i,j}^2 + b_i PT_{i,j} + c_i \tag{1}$$

Considering the VPL effect as a sinusoidal variation the Eq. (1) modifies to (2).

$$FC\left(PT_{i,j}\right) = \sum_{i=1}^{Ns}\sum_{j=1}^{Z} a_i PT_{i,j}^2 + b_i PT_{i,j} + c_i + \left|d_i \times \sin\left(e_i \times \left(PT_{i,\ \min} - PT_{i,j}\right)\right)\right| \tag{2}$$

The prime goal of HTS problem is to reduce the net fuel cost *F* of the thermal plants. Then the objective function is given in (3).

$$Minimize\ F = \sum_{j=1}^{Z}\sum_{i=1}^{N_s} FC\left(PT_{i,j}\right) \tag{3}$$

where the symbols carry the meaning as defined earlier.

The following operational restrictions are to be satisfied.

a. *Load Demand constraints*: It is defined as the balance of the net hydro and thermal generation with the load inclusive of losses in each slot of scheduling j as given in (4)

$$\sum_{i=1}^{N_s} PT_{i,j} + \sum_{i=1}^{N_h} PH_{i,j} = PD_j + PL_j, \text{for } j = 1,2, \dots, Z \tag{4}$$

b. *Generation constraints of Thermal Plant*: The i_{th} thermal generator must operate within the lower and upper bound $PT_{i\,\min}$ and $PT_{i\,\max}$ respectively as shown in (5)

$$PT_{i\,\min} \leq PT_{ij} \leq PT_{i\,\max} \tag{5}$$

c. *Generation constraints of Hydro Plant*: The i_{th} hydro plant generator must operate between its minimum and maximum bounds $PH_{i\,\min}$ and $PH_{i\,\max}$ respectively as given in (6)

$$PH_{i\,\min} \leq PH_{i,j} \leq PH_{i\,\max} \tag{6}$$

d. *Reservoir constraint*: The i_{th} reservoir volume capacity has to lie within the lowest and highest margins as expressed in (7)

$$V_{i\,\min} \leq V_{i,j} \leq V_{i\,\max} \tag{7}$$

e. *Water Discharge constraint*: The flow in m^3, q_{ij}, must be in between the lowest and highest margins as given in (8)

f. *Continuity Equation of Hydraulic Network:* The storage capacity of the reservoir must be in between the lower and higher volume margins as given in (9)

$$V_{i(j+1)} = V_{ij} + \sum_{u=1}^{R_u} \left[q_{u(j-\tau)} + s_{u(j-\tau)} \right] - q_{i(j+1)} - s_{i(j+1)} + r_{i(j+1)} \text{ for } j = 1,2 \dots, Z \tag{8}$$

Where τ is the time gap for water transportation to the reservoir i from its upstream reservoir u at time slot j and R_u is the combination of the upstream hydraulic reservoirs before the hydro plant i

g. *The power generation of the hydro plant PH_{ij}*. It depends on water discharge rate and reservoir storage capacity. It is expressed as in (10)

$$PH_{ij} = c_{1i} V_{ij}^2 + c_{2i} q_{ij}^2 + c_{3i} \left(V_{ij} q_{ij} \right) + c_{4i} V_{ij} + c_{5i} q_{ij} + c_{6i} \tag{9}$$

Where, c_{1i} to c_{6i} are the constants.

3. GWO

GWO is a recent soft computing approach that mimics the social activities of gray wolves. This algorithm depicts leadership, tracking, surrounding and attacking prey

[7] activities of the species. In this algorithm a specific number of gray wolves in a group travel through a multi-dimensional search space in search of prey. The position of gray wolves are considered as different position variables and the distances of the prey from the gray wolves determine the fitness value of the objective function. The individual gray wolf adjusts its position and moves to the better position. The GWO saves the best solutions obtained through the course of iterations. The goal of this algorithm is to reach to the prey by the shortest possible route. The movement of each individual is influenced by four processes. Their hunting mechanism is as follows:

a. The initial step of hunting is to track, chase and approach the prey.

b. The second step is to pursue, move around and harass the prey until it gives up.

c. The last step is to attack prey.

These steps are shown in **Figure 1** [7].

The GWO algorithm was anticipated by Mirjalili et al. [7]. Gray wolves are related to the Canidae family and are zenith predator. A pack approximately consists of a group of 5to12 wolves. Their society is divided on the basis of hierarchy. The leader is a couple called the 'Alphas'. They take all the decisions for the pack and these decisions are then communicated to the pack. All the members of the pack respect the leader with keeping their tails down. The alpha is the best member who can manage the pack in a better way. The second level in this hierarchy is the 'Beta' wolves. It is an assistant wolf next to alpha after the current wolf gone. It assists alpha and keeps discipline in the pack. The third level in this hierarchy is the 'Delta' wolves. The lowest ranked gray wolf is 'Omega'. They are the scapegoat or the babysitters. Amidst all the social hierarchy, there is an exciting social activity of the gray wolf is group hunting (optimization).

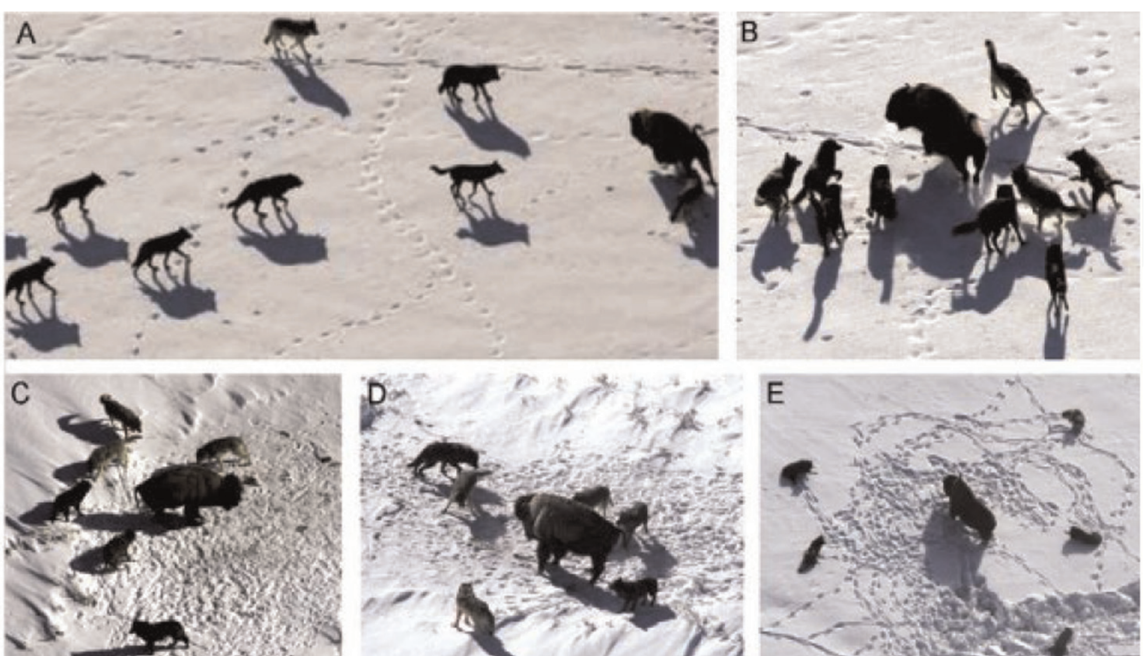

Figure 1.
Hunting steps of Gray Wolf: (A) chasing, approaching and tracking prey (B–D) pursuing, harassing, and encircling (E) Stationary situation and attacking [7].

The encircling behavior of gray wolves may be modeled mathematically as per following Eqs. (11) and (12).

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \tag{10}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{11}$$

Where $\vec{X}_p$ and $\overrightarrow{X}$ are the respective vectors corresponding to the position of the prey and the gray wolf, and t designates the present iteration.

The coefficient vectors $\vec{A}$ and $\vec{C}$ can befound out as given in (13) and (14).

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{12}$$

$$\vec{C} = 2.\vec{r}_2 \tag{13}$$

Where $\vec{r}_1$ and $\vec{r}_2$ vectors are randomly chosen in the range [0, 1], the values of $\vec{a}$ are gradually varied from 2 to 0 with the increase of iteration so as to put emphasis on exploration and exploitation, respectively.

All the wolves of the pack keep updating their locations as per the location of the senior wolves in the pack. Moreover, the location of the prey would be a random place encircled by the alpha, beta and delta during their search because they are more experienced in hunting. The following Eqs. (15)–(17) are proposed to revise the position of all wolves as per the locations obtained so far by the best candidates as the alpha, beta and delta.

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \overrightarrow{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \tag{14}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\left(\vec{D}_\alpha\right), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\left(\vec{D}_\beta\right), \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\left(\vec{D}_\delta\right) \tag{15}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{16}$$

Diverging and converging towards the prey in order to search and attack the prey is what the gray wolves follow. In the mathematical modeling of divergence, we use the value of $|A| > 1$ or $|A| < 1$ for the searching wolf to deviate from the prey to emphasize exploration.

At the beginning of search process, a pack of gray wolves is randomly initialized in the GWO algorithm. Each wolf in the searching place updates its gap from the prey. Finally, the algorithm ends the optimization when termination limit is attained.

4. Quasi opposition based learning

Opposition Based Learning considers both the current and its opposite population simultaneously for getting the best candidate solution. The quasi-opposite population $QOP\left(x_1^{q0}, x_2^{q0}, \dots \dots x_i^{q0}, \dots x_d^{q0}\right)$ in D dimensional region differs from the opposite population as it is the population between the Centre$c$ of the search region and the opposite point x_i^0, expressed as in (18).

$$x_i^{q0} = rand\left(\frac{a_i + b_i}{2}, a_i + b_i - x_i\right) = rand\left(c_i, x_i^0\right); i = 1,2,\ldots d \tag{17}$$

Where, x_i^{q0} is an arbitrary number between c_i and x_i^0.

4.1 QOGWO algorithm for hydrothermal scheduling

The flowchart of the QOGWO to clarify the HTS problem is given in **Figure 2** and the steps are described as follows:

Step 1: Specify the system parameters, the highest and lowest limits of each variable such as $Pop_{\max}$, $q_{\min}$, $q_{\max}$, N_s, N_h, Z, B-coefficient matrix, P_D, $PT_{\min}$, $PT_{\max}$, $PH_{\min}$, $PH_{\max}$' $V_{\min}$, $V_{\max}$, j_r, Cost coefficients and $iter_{\max}$.

Step-2: Initialize randomly the search agents (Gray wolves) among the population and those agents are possible solutions who satisfy the specified constraints.

Step-3: Compute the trial vector (current search agents) $Q_{i,j,k} = [P_1 \ \ P_2 \ldots\ldots P_{POP\max}]$ of the population. The random search agent matrix (P_k) is as in (19).

$$P_k = \begin{bmatrix} q_{11} & q_{12} & \cdots & \cdots & q_{1,Nh} \\ q_{21} & q_{22} & \cdots & \cdots & q_{2,Nh} \\ \cdots & \cdots & \cdots & \cdots & \cdot \\ \cdots & \cdots & q_{ij} & \cdots & q_{i,Nh} \\ q_{Z,1} & \cdots & q_{z,j} & \cdots & q_{Z,Nh} \end{bmatrix} \tag{18}$$

Step 4: The discharge rate $q_{i,d}$ of all the reservoirs for all the slots is taken at random within the bounds and repeatedly adjusted after the check to satisfy the first and last reservoir storage volume which is calculated using (20).

$$q_{i,d} = V_{i,1} - V_{i,25} - \sum_{\substack{j-1 \\ j \neq d}}^{Z} q_{i,j} + \sum_{j-1}^{Z} r_{i,j} + \sum_{u=1}^{R_u} \sum_{j=1}^{Z} q_{u(j-\tau)} \tag{19}$$

Step 5: The volume of each reservoir is calculated by the Eq. (9), and then the hydro generation is scheduled over 24 slots by the Eq. (10).

Step 6: Calculate the thermal power at j_{th} slot using load balance Eq. (4). To satisfy the equation $PT(d,j)$ is taken at random and adjusted using Eq. (21) until it does not defy the limits.

$$B_{dd}PT^2(d,j) + \left(2\sum_{i=1}^{Nh+Ns-1} B_{d,i}.PT(i,\ j) - 1\right)PT(d,j)$$
$$+\left(P_D(j) + \sum_{i=1}^{Nh+Ns-1}\sum_{k=1}^{Nh+Ns-1} PT(i,\ j)B_{i,k}PT(k,\ j) - \sum_{i=1}^{Nh} PH(i,\ j) - \sum_{\substack{i=1 \\ i\neq d}}^{Ns} PT(i,\ j)\right) = 0 \tag{20}$$

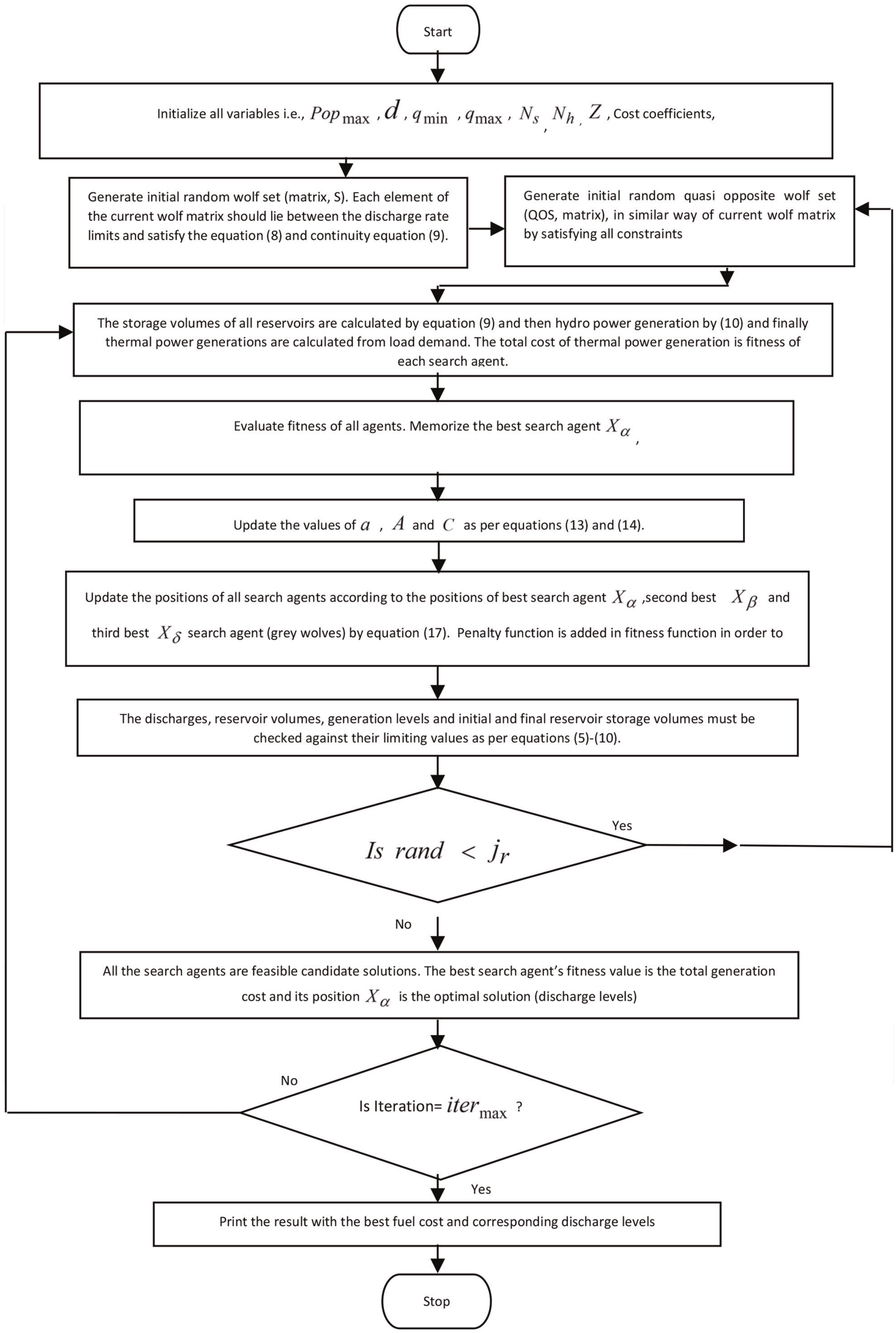

Figure 2.
Flow chart of QOGWO method.

Step 7: The fitness of the solution is evaluated by Eq. (3).

Step 8: Remember the best three search agents X_α, X_β and X_δ (gray wolves) from the population.

Step 9: Revise the values of a, A and C as per Eqs. (13) and (14).
Step 10: According to the positions of best three search agent X_α, X_β and X_δ (gray wolves) all search agents updated their current position by Eq. (17). The violation of constraint is formulated as a penalty added in the fitness function.
Step 11: If the water discharge, the volume of the reservoir and power generations limits are lower than the lowest limit it is assigned the lowest value and if their value exceeds the highest limit, it is assigned the highest value.
Step 12: Select a fresh parameter "jumping rate" (J_r) within the range [0, 1].
If rand $< J_r$, Quasi Opposite set of agents (wolves) can be shaped as below.

$$\begin{array}{c} If\ rand < J_{r.} \\ for\ k = 1 : Pop_{max} \\ for\ i = 1 : Z \\ for\ j = 1 : Nh \\ QOS(:\ ,\ :\ , k) = q(i, j) = rand(c(j), x_0(j)); \\ end \\ end \\ end \end{array} \tag{21}$$

Step 13: Go to Step 2 until the predefined highest iteration number is reached.

5. Result discussion

The projected QOGWO has been used to find the solution of a hydrothermal test system. It has been simulated using MATLAB software. As HTS is a real time problem so, it is necessary that each run of the program should reach close to optimum solution. 20 independent runs are executed to get the optimum solutions for all the algorithms considered here.

5.1 Test system-1

Here the test system-1 is similar to that in [1] but the supplementary data for VPL effect and PDZ of turbines are taken from [2]. Then the fuel cost of the corresponding thermal unit with VPL is given in (22)

$$\begin{aligned} \mathrm{FC}\left(PT_{\mathrm{i,j}}\right) = \sum_{i=1}^{Ns}\sum_{j=1}^{Z} & 0.002PT_{i,j}^2 + 19.2PT_{i,j} + 5000 \\ & + \left|700 \times \sin\left(0.085 \times \left(PT_{i,\ \min} - PT_{i,j}\right)\right)\right| \end{aligned} \tag{22}$$

The respective minimum and maximum thermal generations correspond to 500 and 2500 MW. The water loss in the spillway and the energy loss in catering the load from the hydro plant are ignored. The respective lowest and highest hydro generation correspond to 0 and 500 MW.

Three cases of the test system-1 such as Case 1 (HTS problem considering quadratic cost function only), Case 2 (with PDZ) and Case 3 (with VPL and PDZ) are under study. The several controlling parameters like a, A, C, size of the pack and maximum iteration number have been tried in this algorithm. The values of a, A, C are varied as per Eqs. (13) and (14), the size of the pack is 30 and the maximum iterations took is 500.

5.1.1 Case 1: (HTS problems considering quadratic cost function only)

This is the simplest case where the PDZ of the hydro units and the VPL effect of the steam power plant are neglected. The convergence characteristic in **Figure 3** gives an idea about the working of projected QOGWO approach. From **Figure 3** it is clear that the fuel cost is reduced in 50 numbers of iterations. The considered QOGWO approach takes the computation time of 340.452 s to get the optimal HTS. To validate the proposed QOGWO method, its simulation outcomes are compared in terms of best, average and worst fuel cost over 20 independent runs with the results of other approaches as shown in **Table 1**. The optimal results found by the projected algorithm

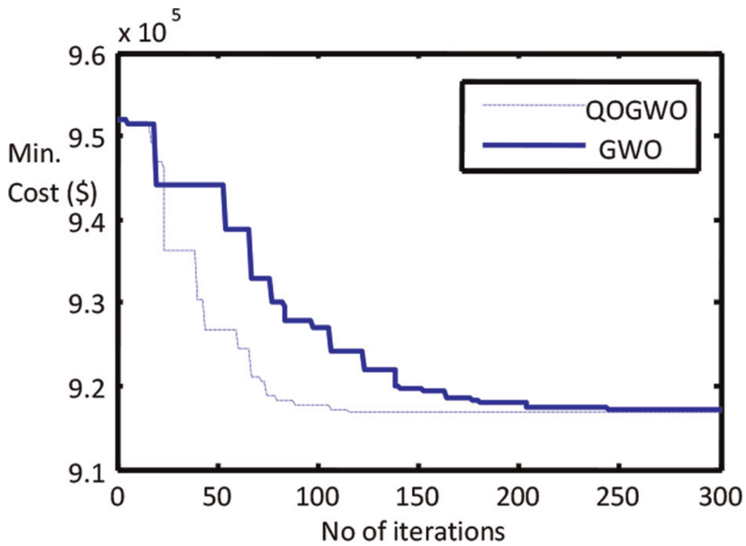

Figure 3.
Convergence features of QOGWO in case-1 of the test system.

Algorithm	Best fuel cost ($)	Average fuel cost ($/day)	Worst fuel cost ($/day)	Variance	Standard deviation	CPU time (sec)
GA [1]	932734.00	936969.00	939734.00	—	—	—
FEP [2]	930267.92	930897.44	931396.81	—	—	—
CEP [2]	930166.25	930373.23	930927.01	—	—	—
IFEP [2]	930129.82	930290.13	930881.92	—	—	1033.20
IPSO [3]	922553.49	—	—	—	—	—
TLBO [4]	922373.39	922462.24	922873.81	—	—	—
SOS [5]	922332.17	922338.20	922482.90	—	—	6.21
GWO	917203.73	917242.58	917288.03	0.0127	0.1128	353.224
QOGWO	916795.74	916812.67	916829.28	0.0096	0.0982	340.452

Table 1.
Comparison of optimal costs for the test system (case 1) after 20 independent runs.

are contrasted with other referred results shown in **Table 1**. It is clear that the QOGWO founded superior result than the above-mentioned accessible techniques. Though SOS has taken less time with a smaller number of iterations and population size, it gives the minimum cost but its minimum is higher than that by GWO and QOGWO.

5.1.2 Case 2: (with PDZ)

The PDZs of reservoirs of hydro power units have taken into account to ensure the viability of the projected method. This case has not been dealt with by many researchers but it is an important case for operation. The results of the proposed method QOGWO are compared in terms of best, average and worst fuel cost over 20 independent runs with the results of other approaches as shown in **Table 2**. It is observed that the QOGWO decreased the minimum, average and worst costs at less execution time than those obtained by the other existing techniques when population size and iterations are similar. The cost convergence feature of QOGWO algorithm is revealed in **Figure 4**.

5.1.3 Case 3: (with VPL and PDZ)

Now the VPL of thermal power units and PDZ of hydro power units are included to confirm the robustness of the projected algorithm. The best rates of hydro

Algorithm	Best fuel cost ($/day)	Average fuel cost ($/day)	Worst fuel cost ($/day)	Variance	Standard deviation	CPU time (s)
IPSO [3]	923443.17	—	—	—	—	—
TLBO [4]	923041.91	—	—	—	—	—
SOS [5]	922844.78	922867.24	923125.44	—	—	9.53
GWO	923146.941	923187.45	923239.50	0.0129	0.1138	321.47
QOGWO	922736.233	922764.186	922810.58	0.0087	0.0932	310.941

Table 2.
Comparison of optimal costs in case-2 for the test system (case 2) after 20 independent runs.

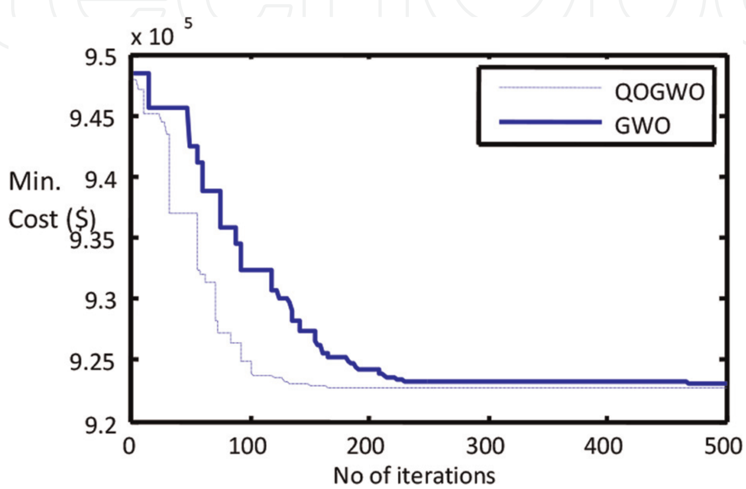

Figure 4.
Convergence features of QOGWO in case-2 of the test system.

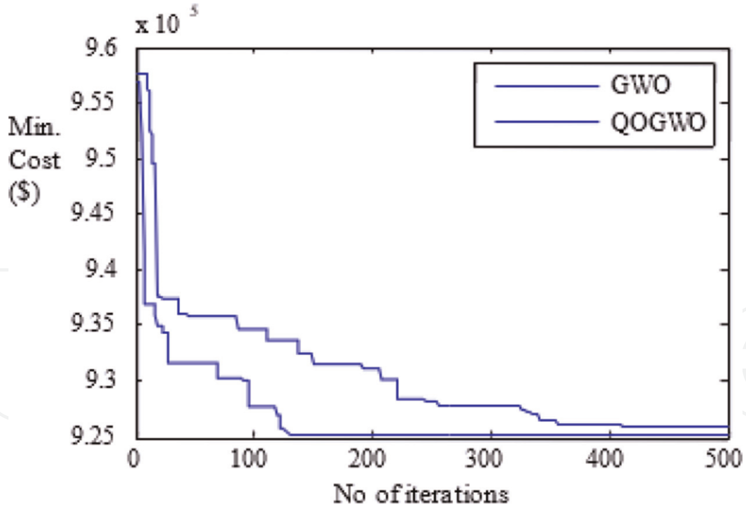

Figure 5(a).
Convergence features of QOGWO in Case-3 of the test system.

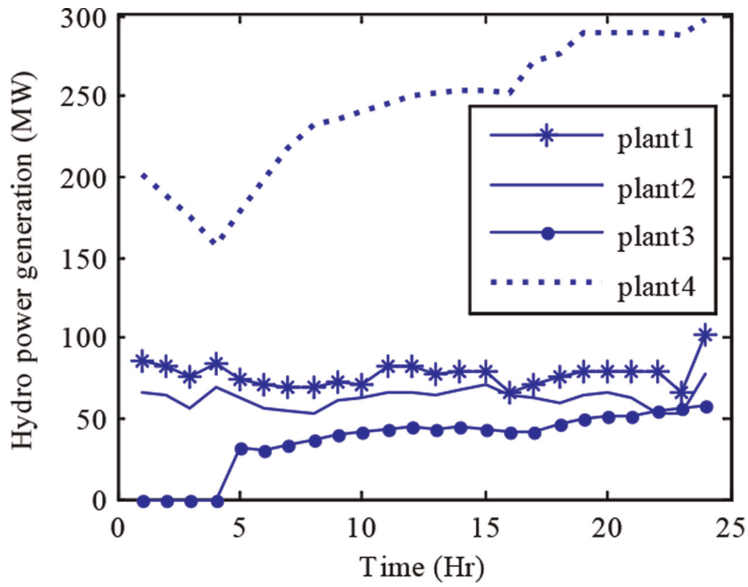

Figure 5(b).
Hourly hydro power generation obtained by QOGWO in Case-3 of the system.

discharges in slots got by the projected QOGWO are shown in **Table 3**. The convergence plot attained by QOGWO is illustrated in **Figure 5(a)**, respectively. In this case, the hourly hydropower generations found by the QOGWO method are given in **Figure 5(b)**.

6. Conclusion

In this study, an effective GWO algorithm is united with quasi-oppositional based learning (QOGWO) has been effectively implemented to solve a hydrothermal test system with quadratic nonlinear cost functions. Progressive improvement of the computational efficiency and better convergence characteristics are attained by quasi-oppositional based learning introduced in the conventional GWO algorithm. It is observed that the simulation time for the same number of iterations and the net cost of generation got by the presented QOGWO for the day is lower than others in all the

Time	Q1	Q2	Q3	Q4	PT (MW)	Time	Q1	Q2	Q3	Q4	PT (MW)
1	9.8564	8.9223	29.7264	13.0645	1017.4263	13	7.9960	8.2150	15.5132	13.4658	1793.6003
2	9.4124	8.5691	29.7217	13.0808	1054.3506	14	7.9872	8.9049	15.9866	13.5550	1756.6392
3	7.9999	6.9965	29.4505	13.1635	1054.1838	15	7.9941	9.5532	16.6901	13.6818	1682.7095
4	9.7886	9.1209	28.6931	13.1236	980.4384	16	6.2264	8.5121	17.5552	13.4527	1645.7608
5	7.9964	8.0000	17.1239	13.1762	943.5170	17	6.7799	8.3072	17.3486	15.5098	1682.7143
6	7.6541	7.0000	17.8867	13.0704	1054.3930	18	7.4033	8.0123	16.0462	15.9873	1682.7161
7	7.3230	6.8335	17.3717	13.1604	1276.1570	19	7.9990	9.0929	14.6481	18.0022	1756.5899
8	7.1700	6.6590	16.3193	13.0902	1608.7928	20	7.9991	9.7041	13.7816	18.0023	1793.5605
9	7.5358	8.0000	15.1289	13.0824	1830.5059	21	7.9973	9.1118	10.0840	18.0004	1756.6036
10	7.2597	8.0000	14.5053	13.1423	1904.4793	22	7.9455	6.9873	10.0585	18.3834	1645.7585
11	9.0105	8.4733	13.5320	13.1777	1793.5797	23	6.1837	6.9939	10.3479	18.9757	1387.0315
12	9.0073	8.4597	13.8286	13.4527	1867.5039	24	12.4744	13.5710	11.7416	22.8566	1054.3990

Table 3.
Hourly hydro discharges ($\times 10^4 m^3$) of the test system in case-3.

systems with the different level of complexities because of well-balanced exploration and exploitation of the QOGWO algorithm. The maximum cases of hydrothermal scheduling studied here in comparison to the existing works can be referred by researchers in future. The consistent performance of QOGWO in the large dimension of the problem with multiple constraints exposes its potential for application in other engineering domains for constrained nonlinear non-convex engineering optimization.

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