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Research Note

Optimal scheduling of hydrothermal system considering variable nature of water transportation delay

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Abstract. This paper presents an algorithm called Grasshopper optimization for solving short-term hydrothermal scheduling problem. The objective of this problem is to reduce the generation cost by optimizing the output of power generation of different thermal and hydro plants for a certain time interval. A non-linear relationship between hydropower generation, net head, and rate of water discharge is considered here. A complex piecewise output limit and head-sensitive conversion of water-to-power is applied here. To investigate the performance of this new technique, three test systems have been considered. The results obtained by this Grasshopper optimization algorithm are compared with those of other well-known soft computing techniques. The efficacy of this proposed technique was verified after comparison with other similar soft techniques.

1. Introduction

A great challenge faced by the power sectors in recent years remains high costs of fuel generation and the objective is to reduce the consumption of fossil fuel. In modern power systems, a large number of generating plants of various types are scheduled to deliver power to load centers. The objective of Hydrothermal Scheduling (HTS) is to generate power optimally so as to minimize the production cost of thermal units while satisfying various constraints including limits of hydro discharge, thermal and hydropower generation limit, availability of water, and power balance. Various inequality and equality constraints and valve point effect must be included in a practical HTS problem. Therefore, the resulting HTS becomes a problem of non-convex optimization. It is still difficult to solve this problem by traditional methods such as Dynamic Programming (DP) [1], gradient search [2], Non-Linear Programming (NLP) [3], Lagrange multiplier method [4], Mixed Integer Linear Programming (MILP) [5], or any other suitable method. DP is quite popular as compared to other classical methods. However, the main drawback of DP is that its computational time increases rapidly following an increase in system size. Linear programming can be applied if the characteristic of fuel cost is quadratic. The main disadvantage of MILP is that the simulation time and memory size increase exponentially when more integer values are incorporated.

Therefore, in recent years, various soft computing methods have been proposed for solving various HTS problems. In 1994, Wong and Wong proposed Simulated Annealing (SA) [6] method to solve short-term HTS problems. Various constraints such as power balance constraints, volume limits of reservoir, and water discharge constraints were considered. In order to check the limits, a relaxation technique was incorporated in the algorithm. The results obtained by this

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method showed that this algorithm had the capability to attain global optimal solution. A coarse-grained parallel SA technique was developed by Wong and Wong [7] for solving HTS problems. The performance of this method was investigated using a test example and it was observed that the results obtained by this technique were better than those of the sequential SA method. However, the main drawback of SA method is that its convergence speed is low and the tuning of parameters is a challenging task. In 1996, Chen and Chang introduced Genetic algorithm (GA) [8] for scheduling of the hydraulically coupled plant. The hydrothermal iteration and successive approximation of the reservoir were not required here. Results obtained by this technique revealed that this approach produced a better solution than the other conventional methods. In1998, GA was incorporated by Orero and Irring [9] in HTS problems. It was found that GA gave a better quality solution to the HTS problem considering net head variation and transport delay of water. The biggest limitation of GA is that it cannot give guarantee of optimality and with increase in system size, the quality of solution deteriorates. Therefore, various modifications have been made to improve the efficiency of GA. Gil et al. [10] proposed GA that simultaneously handled the unit commitment, economic dispatch, and coordination of short-term hydrothermal problems. In order to improve the behavior of GA, sets of expert operators were introduced. It was found that this Improved GA (IGA) had the ability to obtain a near-optimal solution in a reasonable time. Kumar and Naresh [11] developed a real coded GA for the solution of the HTS problem. The performance of this method in a cascaded hydrothermal plant was observed considering non-linear function of hydro generation. The binary coded GA was also implemented to check the performance. Both features are the same, except mutation and crossover. Evolutionary Programming (EP) technique was implemented by Hota et al. [12] for HTS problems. The simulation results achieved by EP were compared with SA and gradient search approaches. It was seen that this method provided better quality solution results than the results of SA and gradient search method. In 2013, Sinha et al. [13] proposed a fast EP method for solving HTS problems. Improved Cauchy mutation and Gaussian method were developed to increase the convergence rate and to obtain a good quality solution. It was examined that the solution quality, convergence rate, and computational efficiency of EP method outperform those of other EP methods. Mandal et al. developed Particle Swarm Optimization (PSO) [14] for solving HTS problems. A non-linear relationship among power generation, discharge rate, and net head was considered [14]. Three thermal plants along with four hydro plants were considered. Simulation results revealed that this technique gave a good quality solution than the other well-known optimization methods such as SA and EP. However, the main drawback of PSO is that the solution obtained by this technique tends to get stuck in a local optimal point. In order to overcome the drawbacks of PSO, various modifications and hybridizations were conducted. In 2012, Wang et al. [15] applied improved self-adaptive PSO in order to solve shot-term HTS issues. The evolution direction of particle was dynamically redirected to avoid premature convergence. The effectiveness was validated on a system containing one thermal unit and four hydro units. In 2018, the two-swarm based PSO search method was developed by Cavazzini et al. [16] for solving HTS problems. The adaptive search diversification PSO was modified using a secondary swarm that dealt with infeasible solution, whereas the primary one dealt with a feasible solution [16]. Six test cases were considered here to validate the performance of this new strategy. Differential Evolution (DE) was incorporated by Mandal and Chakraborty [17] for solving short-term hydrothermal problems. The water time delay between the reservoirs was considered. The results obtained by this method were compared with those of other optimization methods [17]. It was observed that DE method was capable of yielding promising results. The major disadvantage of DE method is its slow convergence rate when a large test system is considered. To promote the exploitation and exploration ability of DE, Sivansubramani and Swarup [18] developed an improved DE method for solving HTS problems. In this paper, DE was hybridized with Sequential Quadratic Programming (SQP) where DE enhanced the exploration capability. In 2014, Basu introduced an improved DE [19] for solving short-term HTS problems. In order to improve search efficiency, Gaussian random variable was used instead of scaling factor. Basu [20] proposed Hopfield neural networks to solve fixed head hydrothermal problems. Results obtained by this method show that this technique enjoyed the capability to obtain a near-optimal solution. Similarly, in recent years, various metaheuristic and heuristic methods and their hybridized forms like Teaching Learning Based Optimization (TLBO) [21], quasi-oppositional TLBO (OTLBO) [22], Cuckoo Search Algorithm (CSA) [23], Multi-Objective Artificial Bee Colony optimization (MOABC) [24], Symbiotic Organisms Search (SOS) [25], Chemical Reaction Optimization (CRO) [26], Grey Wolf Optimizer (GWO) [27], Real Coded Chemical Reaction Optimization (RCCRO) [28], Krill herd algorithm [29], clonal section algorithm [30], flower pollination algorithm [31], sine cosine algorithm [32], Ant Lion Optimizer (ALO) [33], Whale Optimization Algorithm (WOA) [34], Modified CSA [35], Quasi-Reflected Symbiotic Organisms Search (QRSOS) [36], quasi-reflected ions motion optimization [37], improved predator influenced civilized swarm optimization [16,38], Real Coded Genetic Algorithm with Artificial Fish Swarm Algorithm (RCGA-AFSA) [39], ORCCRO [40], Modified Chaotic Differential Evolution (MCDE) [41], modified dynamic neighbourhood learning based PSO [42], hybrid CRO [43], Non-dominated Sorting Gravitational Search Algorithm integrated with Disruption operator (NSGSA-D) [44], Hybridized gravitational search algorithm [45], Parallel Multi-Objective Differential Evolution (PMODE) [46], Hybrid Particle Swarm Optimization approach with Small Population size (HPSO-SP) [47], Quasi-Oppositional Group Search Optimization (QOGSO) [48], Parallel multi-objective GA [49], Improved harmony search algorithm [50], adaptive selective CSA [51], couple-based PSO [52], improved cloud adaptive quantum-inspired binary social spider optimization algorithm [53], and hybrid ABC-BAT algorithm [54] have been applied to short-term hydrothermal problems to ensure a faster convergence speed and achieve near-optimal solutions.

In 2017, Grasshopper Optimization Algorithm (GOA) [55] was proposed by Saremi et al. for solving structural problems. This optimization method functions based on the grasshopper swarm activities [55]. The observations made by this method were compared to those of various well-known methods. It was found that the proposed method provided a better quality solution than other optimization techniques. The advantages of GOA method are as follows:

- In nature, grasshoppers conduct extensive exploration by avoiding contact with each other. Thus, the algorithm can avoid local optima [55];
- High exploitation and convergence results in this algorithm due to the attraction between grasshopper and the comfort zone were adopted by them [55];
- High attraction between grasshoppers and also the adaptive nature of the co-efficient of comfort zone help make a balance between the exploration and exploitation properties [55];
- GOA exhibits a high exploitation ability while solving problems involving unimodal test functions. For multi-modal test functions, it will be very effective between exploration and exploitation while finding a solution to problems having composite functions. For all these qualities, GOA remarkably outperforms many recent algorithms while solving a wide variety of optimization problems [55].

In this paper, authors have applied GOA to solve the short-term HTS problem [36]. In order to check the feasibility of this algorithm, two test systems have been considered. It is observed that the result obtained by this GOA method is superior than those of the other well-known algorithms. The main contributions of this paper are as follows:

- In most of the HTS problems, a fixed value of water transportation delay is generally considered which is not a practical one. The transportation delay varies with a hydro reservoir discharge rate. It is a non-linear water discharge function. In this work, the non-linearity of water transportation delay with the discharge rate of water has been considered. This is a real aspect of operation in HTS;
- Hydropower generation mainly depends on the volume of water. In the conventional method of HTS, the volume of water is considered that may not match with the realistic condition. In this paper, a different approach has been adopted to consider the volume of water represented by three different sets of equations categorized into three segments [56];
- Water transportation delay has been incorporated in this proposed method of HTS.

2. Problem formulation

2.1. Objective function

The main objective of HTS is to reduce the cost of the generation of thermal power units while satisfying various inequality and equality constraints [25]. The price of hydro power units is negligible [36]. The fitness function of HTS problem is given below [36]:

$$\min C_T = \sum_{I=1}^{NT} \sum_{t=1}^{TN} F_I(TH_p(I,t)), \tag{1}$$

where NT is the number of thermal units. TN represents the number of intervals [36]. TH_p indicates power generation of thermal unit of the Ith plant at time interval t [25]. The cost function of thermal plants without considering valve point effect is represented by the following equation [36]:

$$F_I(TH_p(I,t)) = \alpha_{Is} + \beta_{Is} \times TH_p(I,t) + \gamma_{Is} \times TH_p^2(I,t). \tag{2}$$

The cost function of thermal plants considering valve point effect can be represented by the following equation [36,57]:

$$F(TH_p(I,t)) = \alpha_{Is} + \beta_{Is} \times TH_p(I,t) + \gamma_{Is} \times TH_p^2(I,t) + \left| \begin{array}{l} \delta_{Is} \times \sin(\varepsilon_{Is}. \\ (TH_p^{\min}(I) \\ -TH_p(I,t))) \end{array} \right|$$

$$I = 1, 2, \cdots, NT, \qquad t = 1, 2, ..., TN, \tag{3}$$

where α_{Is}, β_{Is}, γ_{Is}, δ_{Is}, and ε_{Is} represent fuel cost coefficients of the Ith thermal unit and ($TH_p^{\min}(I)$ indicates the minimum limit of the thermal power generation.

2.2. Equality and inequality constraints

Various constraints associated with HTS problems are given below.

2.2.1. Continuity constraints of hydraulic network

The reservoir flow balance or the equation [58] of continuity depends on the transportation delay between two reservoirs. The equation of flow balance relates to the previous interval with net discharge [58], and inflow and storage volume of hydro reservoir of the present interval. The volume of water at time interval t must satisfy the following equation [36]:

$$\begin{aligned} VO_h(i,t) = & VO_h(i,t-1) + IN_h(i,t) \\ & - DI_h(i,t) + \sum_{m \in Y_u(i)} DI_h(m, t-\tau_m) \end{aligned}$$

$$i = 1,2,\cdots,NH \qquad t = 1,2,\cdots,TN, \tag{4}$$

where $VO_h(i,t)$, $IN_h(i,t)$, and $DI_h(i,t)$ denote the final hydro reservoir storage volume, inflow rate, and discharge of hydro reservoir of the ith hydro plant at time interval t, respectively [25,36]. NH represents the total number of hydro unit numbers [25]; τ_m is the delay of water transport [25]. $Y_u(i)$ denotes the upstream plants numbers which are above and connected to hydro unit i [36].

2.2.2. Limits of discharge and storage volume of hydro reservoir

The amount of water discharge for any particular reservoir should not violate the lower and upper limits of water discharge because these reservoirs are used to supply water for farming and other purposes [36].

$$VO_h^{\min}(i) \leq VO_h(i,t) \leq VO_h^{\max}(i). \tag{5}$$

The discharge rate of hydro plants must lie within their minimum and maximum discharge levels [36].

$$DI_h^{\min}(i) \leq DI_h(i,t) \leq DI_h^{\max}(i)$$

$$i = 1,2,...,NH, \qquad t = 1,2,...,TN, \tag{6}$$

where $VO_h^{\min}(i)$, $VO_h^{\max}(i)$ represent the lower and upper limits of the ith hydro reservoir storage volume [36]. $DI_h^{\min}(i)$, $DI_h^{\max}(i)$ indicate the lower and upper limits of water discharge of the ith hydro reservoir [36].

2.2.3. Initial and terminal reservoir storage limits

This is generally set by the mid-term scheduling process. This equality constraint implies that the total quantity of available water is fully utilized. Initial and final reservoir volumes are given by [36]:

$$VO_h(i,0) = VO_h^{begin}(i), \tag{7}$$

$$VO_h(i,TN) = VO_h^{end}(i),$$

$$i = 1,2,...,NH, \tag{8}$$

where VO_h^{begin} and VO_h^{end} denote the initial and terminal storage volumes of the ith hydro reservoir.

2.2.4. Prohibited discharge zones

The reservoir of hydro plant may have a certain discharge zone where the operation of hydro units is restricted [27,36] because vibrations in the components at certain power output are observed. It is found that when the vibration frequency equals the natural frequency, resonance occurs [36]. This can harm the apparatus. The rate of discharge of hydro reservoir including prohibited discharge zone can be represented as follows [36]:

$$DI_h(i) \in \begin{cases} DI_h^{\min}(i) \leq DI_h(i,t) \leq DI_h^{L,(1)}(i) \\ DI_h^{U(u-1)}(i) \leq DI_h(i,t) \leq DI_h^{L(u)}(i) \\ DI_h^{U(PZ)}(i) \leq DI_h(i,t) \leq DI_h^{\max}(i) \end{cases}$$

$$u = 2,3,\cdots,PZ, \tag{9}$$

where $DI_h^L(i,t)$ and $DI_h^U(i,t)$ are the minimum and maximum limits of the uth prohibited zones of hydro plant i [36]. PZ indicates the number of the prohibited discharge zones.

2.2.5. Limits of generations

The total number of thermal and hydro power generations should not exceed the lower and upper limits of generation, which are represented by the following equations [36]:

$$TH_p^{\min}(I) \leq TH_p(I,t) \leq TH_p^{\max}(I)$$

$$I = 1,2,\ldots,NT, \qquad t = 1,2,...,TN, \tag{10}$$

where $TH_p^{\min}(I)$, $TH_p^{\max}(I)$ are the minimum and maximum generation limits of the Ith thermal unit.

$$HR_p^{\min}(i) \leq HR_p(i,t) \leq HR_p^{\max}(i)$$

$$i = 1,2,\ldots,NH, \quad t = 1,2,\ldots,TN, \tag{11}$$

where $HR_p(i,t)$ is the output of the ith hydro plant at time interval t. $HR_p^{\min}(i)$, $HR_p^{\max}(i)$ indicate the lower and upper power output limits of the ith hydro unit [36]. The hydropower generation is a function of storage volume and discharge of water, which is represented as follows [36]:

$$\begin{aligned} HR_p(i,t) = & W_{1i} \times VO_h^2(i,t) \\ & + W_{2i} \times DI_h^2(i,t) + W_{3i} \times VO_h(i,t) \\ & \times DI_h(i,t) + W_{4i} \times VO_h(i,t) \\ & + W_{5i} \times DI_h(i,t) + W_{6i} \end{aligned}$$

$$i = 1, 2, \cdots, NH, \qquad t = 1, 2, \cdots, TN, \tag{12}$$

where W_{1i}, W_{2i}, W_{3i}, W_{4i}, W_{5i}, and W_{6i} are the coefficients of generation.

2.2.6. Power balance constraints

Total power generation by thermal and hydro units at any time interval t must satisfy the load demand and loss of the system at particular interval of time [36]. This equation can be represented by the following equation [36,58]:

$$\sum_{I=1}^{NT} TH_p(I,t) + \sum_{i=1}^{NH} HR_p(i,t) = PO_{Demand}(t) + PO_{Loss}(t), \tag{13}$$

where $PO_{Demand}(t)$ and $PO_{Loss}(t)$ represent the load demand and transmission losses at time interval t [58].

2.2.7. Equations of water-to-power conversion

Hydropower generation can be calculated based on the volume segment of water due to dependency of hydro power generation mainly on the water volume. The hydropower generation characteristic may be represented by a linear water-to-power conversion curve [56] by assuming the storage reservoir volume as constant. This curve shows the relation of the discharge of input water DI_h to the generation of power output TH_p, as depicted in Figure 1 [56]. Linear fitting method is used to formulate the linear function when the volume of water is at the interval n [56]. The water-to-power conversion function can be represented as follows [56]:

$$HR_p(i,t) = e_{h,n}(i,t) \times DI_h(i,t) + f_{h,n}(i,t)$$

$$\mathrm{V}_{h,n-1} \le VO_h \le V_{h,n}, \quad HR_{h,t} \ge 0, \tag{14}$$

where $HR_p(i,t)$ represents hydro power output of unit i at time interval t [56]. $e_{h,n}(i,t)$ is the water-to-power conversion slope of hydropower plant i in volume segment n; $f_{h,n}(i,t)$ represents the water-to-power conversion intercept of hydropower plant i in volume segment n. $VO_h(i,t)$ indicates the volume of storage of unit i in the n segment of water-to-power conversion constraints [56]. In Figure 1, $DI'_{h,t,n}$ indicates one section of $DI_{h,t,n}$ [$DI_{h,t,n}$ is the discharge of water of hydropower plant in the nth volume segment at time t which is divided into two sections (in m^3/s)] and the value of range is [0, $-f_{h,n}/e_{h,n}$]. $DI''_{h,t,n}$ is another section of $DI_{h,t,n}$ (in m^3/s) and the value of range is [0, $\max(0, DI_{h,t,n} + f_{h,n}/e_{h,n})$] [56].

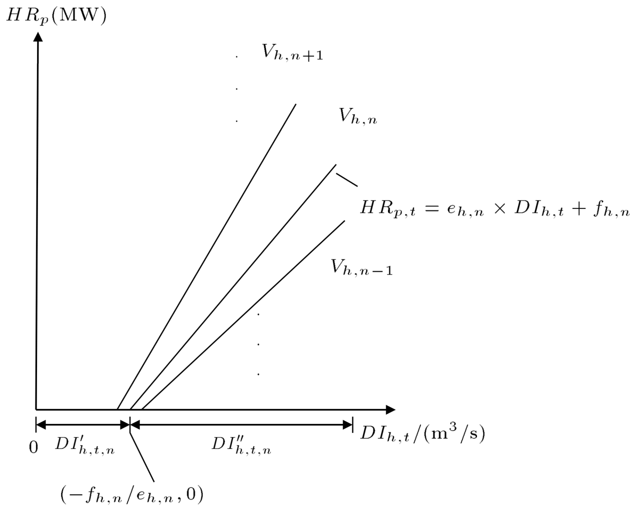

Figure 1. Hydropower generation curve.

2.2.8. Limits of piecewise output power

The power output of hydro units is different as the output of hydro plants is based on the reservoirs' volume. Therefore, the limits of power related to the reservoir volume may be expressed by the following equations [56]:

$$\underline{HR}_p(i,t) = \underline{HR}_p(i,s)$$

$$VO_{h,s-1}, \le VO_h(i,t) \le VO_{h,s}\ , \tag{15}$$

$$\overline{HR}_p(i,t) = \min(HR_{p,\max}, \overline{HR}_p(i,s)),$$

$$\mathrm{VO}_{h,s-1} \le VO_h(i,t) \le VO_{h,s}$$

$$i \in \{1,2,3,...,NH\} \quad \text{and} \quad s \in \{1,2,3,...,S\}, \tag{16}$$

where s indicates the piecewise water volume index within power limits [56]. S is the segment number. $\underline{HR}_p(i,t)$ and $\overline{HR}_p(i,t)$ are the lower and upper limits of hydro power of unit I at the tth time interval [56]. $HR_p(i,s)$ and $\overline{HR}_p(i,s)$ are the lower and upper limits of power of unit i at volume interval s [56].

2.2.9. Impact of water time delay

The water time delay of flow between upstream and downstream reservoirs is influenced by outflow of water of upstream reservoir for constant natural inflow [56]. The time delay of water flow between upstream and downstream reservoirs can be shortened if water outflow of upstream reservoir increases [56]. Therefore, delay time of water flow is not constant [56]. However, it is found that the problems become very difficult if the non-linear function of water time delay is directly used [56]. Therefore, for maintaining the non-linear characteristics of water time delay, the non-linear function of water time delay is discretized by step function [56].

3. Grasshopper Optimization Algorithm (GOA)

Grasshoppers are insects that are considered as pest since they cause harm to crop production [55]. They are found individually in nature and may form a swarm of very large size [55], the unique aspect being that they can form a swarm both in nymph and adulthood [55]. In the nymph stage, they jump and move in the huge group like rolling cylinders and eat almost all vegetation, while they form a swarm in the air in adulthood. Thus, they migrate from one place to another. In the nymph stage, the movement is slow and in small steps which enhances its exploitation ability. In adulthood, long-range movement of abrupt nature is found, which enhances exploration capability of grasshoppers. Thus, exploitation and exploration are both present as natural characteristics of grasshoppers. One more important characteristic of grasshopper swarm is searching for food source [55]. The characteristics of swarming of grasshoppers have been mimicked in GOA. The mathematical model of GOA is as follows [55]:

$$P_i = Soc_i + G_i + W_i, \tag{17}$$

where P_i is the ith grasshopper's position, Soc_i stands for the social interaction, G_i denotes the force of gravity on the ith grasshopper, and W_i represents the wind advection. In order to project randomness, the equation may be represented as [55]:

$$P_i = rand_1 Soc_i + rand_2 G_i + rand_3 W_i,$$

where $rand_1$, $rand_2$, $rand_3$, represent random numbers in between [0, 1] [55].

$$Soc_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} k\left(y_{ij}\right)\hat{y}_{ij}, \tag{18}$$

where $y_{ij} = |p_j - p_i|$ represents the distance between the jth and ith grasshoppers; $\hat{y}_{ij} = \frac{p_j - p_i}{y_{ij}}$ indicates a unit vector from the jth and ith grasshoppers [55]; and N is the number of grasshoppers. k is a function defining the strength of social forces which is given by [55]:

$$k(r) = ae^{\frac{-r}{l_a}} - e^{-r}, \tag{19}$$

where a denotes the intensity of attraction and l_a stands for the attractive length scale.

$$G_i = -g\, y\hat{e}_v, \tag{20}$$

where g indicates the gravitational constant and $\hat{e}_v$ represents a unity vector towards the centre of earth [55].

$$W_i = u\,\hat{e}_w, \tag{21}$$

where u indicates a constant drift and $\hat{e}_w$ denotes a unit vector in the wind direction [55]. Since there is no wing in nymph grasshoppers, the movement of these depends largely on the direction of wind [55].

Substituting the values of Soc, G, and W in Eq. (17), we have:

$$P_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} s\left(|p_j - p_i|\right)\frac{p_j - p_i}{y_{ij}} - g\, d\hat{e}_v + u\,\hat{e}_w. \tag{22}$$

However, using this mathematical model, the grasshoppers reach the comfort zone quickly and convergence of the swarm to a specific point does not occur [55]. To overcome these limitations in solving optimization problems, the equation is modified as follows [55]:

$$P_i{}^d = C\left(\sum_{\substack{j=1 \\ j\neq i}}^{N} C\frac{ub_d - lb_d}{2} s\left(\left|p_j{}^d - p_i{}^d\right|\right)\frac{p_j - p_i}{y_{ij}}\right) + \hat{T}_d, \tag{23}$$

where ub_d is the upper bound, while lb_d is the lower bound in the Dth dimension [55]. $\hat{T}_d$ is the value of the Dth dimension in the target (best solution found so far), and C is a decreasing coefficient to shrink the comfort zone, repulsion zone, and attraction zone. The first C in Eq. (23) balances exploration and exploitation of the entire swarm around the target. The second C decreases the attraction zone, comfort zone, and repulsion zone between grasshoppers. To balance exploration and exploitation, the parameter C needs to be reduced proportional to the number of iterations. This mechanism promotes exploitation with increase in iteration count. The coefficient C reduces the comfort zone proportional to the number of iterations and is expressed as follows [55]:

$$C = C_{\max} - b\frac{C_{\max} - C_{\min}}{B}, \tag{24}$$

where $C_{\max}$ and $C_{\min}$ denote the maximum and minimum values, respectively, b is the current iteration, and B represents the maximum number of iterations.

In the proposed model, the grasshoppers require moving gradually towards a target (point of convergence) during the iteration process [55]. In a real search space, the global optimum being unknown, there is no fixed target. Hence, in each step of optimization, a target needs to be found. The fittest grasshopper, i.e., the one corresponding to the best solution, is considered as target during the optimization process; and all the grasshoppers move towards that target in order to find a better and more accurate target in the search space. The pseudo code of GOA may be found in [55].

3.1. Algorithm

The flowchart of GOA algorithm is explained in Figure 2 which shows the application of GOA method in HTS problems. The steps of the GOA method applied to HTS problems are given below:

1. Initialize the number of thermal and hydropower units and their specified limits. Specify the water volume limit as well as the initial and final storages of reservoir.
2. Initialize GOA parameters like $C_{\max}$, $C_{\min}$ and maximum iteration number.
3. Generate an initial population matrix (hydro discharges) randomly up to $(TN-1)$ interval:

$$DI_h^{TN-1}(i,t)=(DI_h^{\max}-DI_h^{\min})\times rand+DI_h^{\min}$$
$$t=1,2,3,...,T_{N-1}. \tag{25}$$

4. Calculate volume of reservoir for each interval using hydro discharge values using Eq. (4).
5. Check the constraints limit using Eq. (5). If all constraints are satisfied, then go to step 6. Otherwise, go to step 3.
6. Calculate the generation of hydropower for each unit using Eqs. (14) and (16).
7. Calculate the hydro discharges at TNth intervals for each reservoir. The equation used to calculate discharge of $Y_u(i)$ number of reservoirs which do not have any upstream reservoir is given below [36]:

$$DI_h(i,t)=VO_h(i,t-1)-VO_h(i,final)+IN_h(i,t). \tag{26}$$

To calculate the discharge of the reservoir having a connected upstream reservoir, the following equation is used [36].

$$DI_h(i,t)=VO_h(i,t-1)-VO_h(i,final)+IN_h(i,t)+\sum_{m\in Y_u(i)} DI_h(m,t-\tau_m). \tag{27}$$

8. Check the constraint limits of discharges of all hydro reservoirs at TNth time interval. If all constraints are satisfied, then calculate the hydropower generation at TNth interval using Eq. (14).

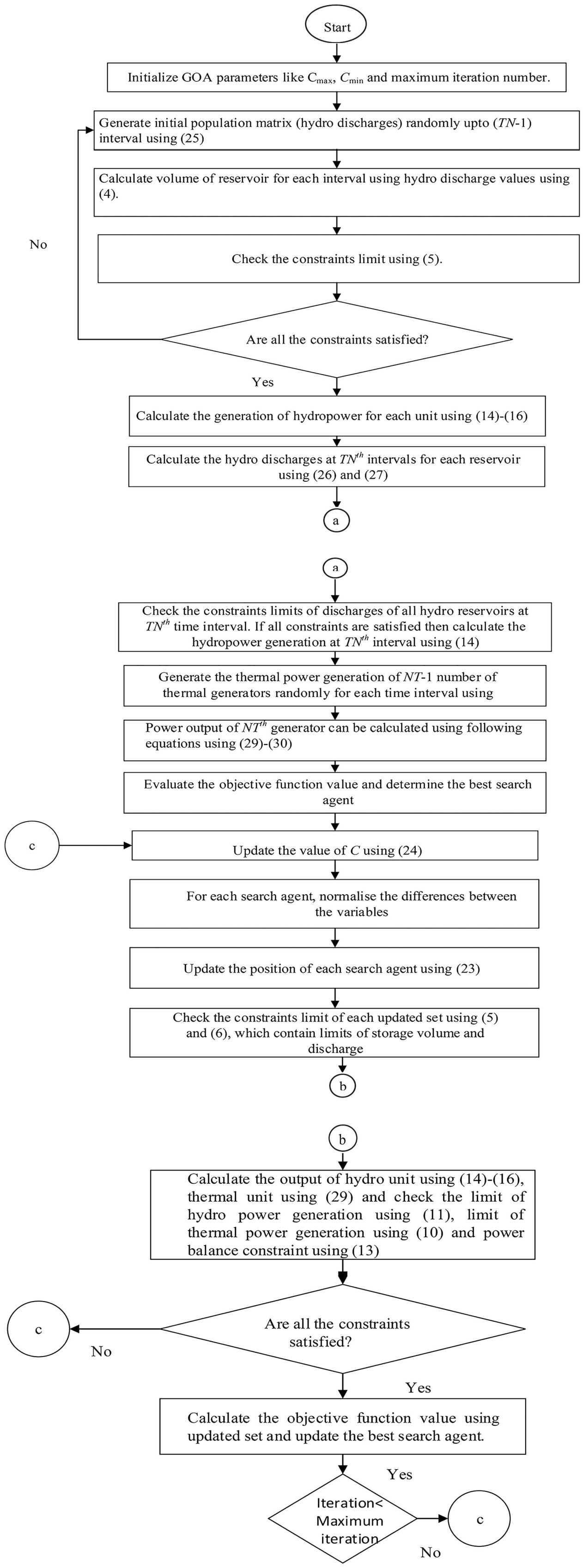

Figure 2. Flow chart of Grasshopper Optimization Algorithm (GOA) applied to Hydrothermal Scheduling (HTS) problem.

9. Generate the thermal power generation of $NT-1$ number of thermal generators randomly for each time interval using the following equation [36]:

$$TH_p^{NT-1}(i,t) = (TH_p^{\max} - TH_p^{\min}) \times rand + TH_p^{\min}. \quad (28)$$

10. Power output of the NTth generator can be calculated using the following equations:

$$TH_{Demand}(t) = PO_{Demand}(t) - \sum_{i=1}^{NH} HR_p(i,t)$$

$$\text{for } t = 1,2,...,TN, \quad (29)$$

$$TH_p^{NT}(t) = TH_{Demand}(t) - \left[\sum_{I=1}^{NT-1} TH_p(i,t)\right]. \quad (30)$$

The decision variable matrix can be represented by:

$$P = \begin{bmatrix} DI_h^{(1,1)} DI_h^{(2,1)} DI_h^{(3,1)} ... DI_h^{(NH,1)} \\ DI_h^{(1,2)} DI_h^{(2,2)} DI_h^{(3,1)} ... DI_h^{(NH,2)} ... \\ \\ DI_h^{(1,TN)} DI_h^{(2,TN)} DI_h^{(3,TN)} ... DI_h^{(NH,TN)} \\ TH_p^{(1,1)} TH_p^{(2,1)} ... TH_p^{(NT,1)} \\ TH_p^{(1,2)} TH_p^{(2,2)} ... TH_p^{(NT,2)} \end{bmatrix} \quad (31)$$

11. Evaluate the objective function value.
12. Update the value of C using Eq. (24).
13. For each search agent, normalize the differences between the variables.
14. Update the position of each search agent using Eq. (23).
15. Check the constraints limit of each updated set using Eqs. (5) and (6), which contain limits of storage volume and discharge.
16. Calculate the output of hydro unit using Eqs. (14) and (16) as well as thermal unit using Eq. (29); check the limit of hydro power generation using Eq. (11), limit of thermal power generation using Eq. (10), and power balance constraint using Eq. (13). If all constraints are satisfied, then go to step 17; otherwise, go to step 13.
17. Calculate the objective function value using updated set.
18. If the solution obtained with the updated set is better, store the updated set and the corresponding solution.
19. Repeat steps (12)-(18) until the termination criterion is reached.

4. Simulation results

Two test systems have been considered here in order to check the efficiency, robustness, and solution quality of GOA technique as compared to other well-known soft computing methods such as GA, BBO, DE/BBO, and GWO methods. This algorithm is tested in MATLAB 2009 and executed on a 2.4 GHz core i3 personal computer with 2 GB RAM.

4.1. Experimental design

A practical test system consisting of seven hydro units and eight thermal units has been considered here. This test system is chosen because it is easier to check the feasibility of test results if a real system is considered. On the other hand, other test systems are considered to check the feasibility of the GOA algorithms as compared to other soft techniques. This algorithm is tested on small and large test systems to check whether the performance of GOA algorithm is satisfactory or not. Therefore, the main reason of choosing different test systems with different numbers of thermal and hydro units is to check the efficiency and robustness of the proposed algorithm as compared to other technique like GA, BBO, DE/BBO, and GWO.

4.2. Description of test systems

4.2.1. Test system I

Here, seven hydro and two thermal plants have been considered. Transmission loss is neglected. Input data are available in Tables A.1–A.4 in Appendix A. The optimal hourly discharges of water for each hydro plant are shown in Table 1. The hydro and thermal power generations achieved by GOA method are shown in Tables 2 and 3, respectively. The average, best, and maximum costs obtained by GOA and other optimization methods like GA, BBO, DE/BBO, and GWO are mentioned in Table 4. Figure 3 shows the water discharges at different time intervals. The variations of reservoir volume at different time intervals by GOA algorithm are shown in Figure 4. The power outputs of each hydro and thermal unit with variation of load at a regular time interval are shown in Figure 5. The cost convergence curves achieved by GOA, DE/BBO, BBO, GWO, and GA methods are shown in Figure 6.

4.2.2. Test system II

Seven hydro and four thermal plants have been considered in this case. Transmission loss is neglected. Input data are available in Tables A.1–A.4 in Appendix-A. The optimal hourly discharges of water for each hydro plant are mentioned in Table 5. The hydro and thermal power generations achieved by GOA algorithm are shown in Tables 6 and 7, respectively. The mean, best, and worst costs obtained by GOA and other optimization techniques like GA, BBO, DE/BBO, and GWO are described in Table 8.

Table 1. Hourly hydro discharge obtained by Grasshopper Optimization Algorithm (GOA) algorithm for Test system I.

	Hydro discharges (m^3)						
Hour	DI_{h1}	DI_{h2}	DI_{h3}	DI_{h4}	DI_{h5}	DI_{h6}	DI_{h7}
1	40492.91684	39397.08218	97339.87596	80750.85422	327337.4852	489492.6676	468758.2614
2	28093.29614	34578.22238	237968.1313	127436.4753	358805.0142	577060.5733	264723.568
3	39283.42062	33357.98934	167007.2547	89779.40675	265857.9057	627867.6063	393313.7155
4	38303.43181	28622.07277	289145.4146	174011.1573	207011.3191	254338.7261	493995.1209
5	33865.48242	27348.48305	317946.7604	280554.8966	302196.6486	486642.4486	600289.4502
6	42040.85897	25232.59202	100110.5869	250599.2471	425452.6794	601353.943	718392.4352
7	33362.16004	27130.8786	84603.13677	141677.863	191384.5439	448238.61	262036.3969
8	32144.4527	34180.56948	218531.8337	243050.4342	275064.5683	510800.1147	366956.9718
9	25004.5879	28598.84717	128183.0675	122984.6491	261418.5067	300675.7718	486437.6621
10	32107.4448	25883.13269	318289.6232	326711.6211	413722.6835	518630.3465	360505.9557
11	36296.5655	29789.68778	127355.8352	331215.0293	312831.8642	658001.109	328154.8499
12	29734.23896	30952.69852	102535.2686	125897.1541	325171.8651	308449.7636	278318.6428
13	29070.47036	24243.74022	144074.9749	210812.8964	177242.7026	593200.4193	289664.7905
14	30380.11404	40583.65285	252605.3737	226291.5277	423997.6018	322287.3089	497197.1394
15	44555.81211	37198.22025	213666.9677	202712.3944	158710.9667	444352.6154	500660.5803
16	36534.26931	25498.8936	350916.3121	116121.2649	239486.8646	348793.3549	377377.7065
17	34701.02737	38739.45523	90971.72652	175396.678	288448.1593	432865.5973	401111.8063
18	41942.19154	29936.83971	144776.8361	293481.4044	92836.05538	558523.2228	604723.0148
19	39467.67703	40492.49145	169735.0602	187677.4849	347254.3662	368205.6791	199008.6357
20	29250.13918	32274.2464	245007.3438	329630.3315	428973.1089	535747.759	547030.0323
21	28288.61849	22368.02485	345657.2454	260635.1185	197131.0163	436623.1178	284692.9706
22	40365.87295	29542.63642	248723.7633	238157.1698	412305.4278	411687.3309	458348.5022
23	30082.56141	27655.79825	225229.4821	161543.9004	340549.3786	349286.4643	416322.5759
24	29913.06715	29913.06715	354656.2627	354656.2627	354656.2627	709427.3323	709427.3323

Table 2. Hydro power output for Test system I against minimum cost using Grasshopper Optimization Algorithm (GOA).

	Hydro power output (MW)						
Hour	HR_{p1}	HR_{p2}	HR_{p3}	HR_{p4}	HR_{p5}	HR_{p6}	HR_{p7}
1	0.9673	0.9112	1.8412	1.2770	9.6634	13.7745	12.8516
2	0.3325	0.6645	6.6240	2.8648	10.7337	17.6722	3.7700
3	0.9054	0.6020	4.2106	1.5841	7.5725	19.9336	9.4936
4	0.8552	0.3595	8.3645	4.4488	5.5712	3.3078	13.9749
5	0.6280	0.2943	9.3441	8.0724	8.8084	13.6477	18.7061
6	1.0466	0.1860	1.9355	7.0536	13.0003	18.7535	23.9628
7	0.6022	0.2832	1.4081	3.3492	5.0397	11.9383	3.6504
8	0.5399	0.6441	5.9630	6.7968	7.8856	14.7229	8.3205
9	0.1743	0.3583	2.8902	2.7134	7.4215	5.3703	13.6385
10	0.5380	0.2193	9.3557	9.6422	12.6014	15.0714	8.0333
11	0.7525	0.4193	2.8621	9.7953	9.1701	21.2748	6.5934
12	0.4165	0.4789	2.0179	2.8125	9.5898	5.7163	4.3752
13	0.3825	0.1354	3.4307	5.7004	4.5587	18.3906	4.8802
14	0.4495	0.9720	7.1218	6.2269	12.9509	6.3322	14.1174
15	1.1753	0.7986	5.7975	5.4249	3.9285	11.7653	14.2716
16	0.7646	0.1996	10.4654	2.4800	6.6756	7.5120	8.7843
17	0.6708	0.8775	1.6246	4.4959	8.3408	11.2540	9.8407
18	1.0415	0.4268	3.4546	8.5120	1.6881	16.8471	18.9034
19	0.9148	0.9673	4.3034	4.9136	10.3408	8.3760	0.8451
20	0.3917	0.5465	6.8634	9.7414	13.1201	15.8333	16.3355
21	0.3425	0.0393	10.2865	7.3949	5.2351	11.4213	4.6589
22	0.9608	0.4067	6.9898	6.6304	12.5532	10.3114	12.3883
23	0.4343	0.3101	6.1908	4.0248	10.1128	7.5339	10.5177
24	0.4256	0.4256	10.5926	10.5926	10.5926	23.5638	23.5638

Table 3. Thermal power output for Test system I against minimum cost using Grasshopper Optimization Algorithm (GOA).

Hour	**Thermal power output (MW)**	
	TH_{p1}	TH_{p2}
1	507.5069682	501.2066414
2	963.2166106	594.1217663
3	1859.211511	596.4866667
4	1066.274219	596.8437858
5	885.9453059	604.5537908
6	2767.333866	616.7278747
7	1959.5627	514.166251
8	1671.336756	583.7904157
9	1390.339097	577.0942704
10	1867.07321	627.4654552
11	1852.936634	596.1958816
12	1595.957601	578.6354243
13	1344.202782	618.3187792
14	1464.701857	587.1274437
15	1622.716591	534.1215832
16	1493.15729	619.9611817
17	1372.463776	610.4317652
18	1831.16237	597.9641564
19	1903.326233	616.0127159
20	1750.508942	586.6591074
21	1846.824104	563.797408
22	1502.237389	587.5220127
23	1902.371229	558.5044016
24	1858.519642	611.7238002

Figure 7 shows the water discharges at different time intervals. The variations of reservoir volume for each time interval by GOA algorithm are depicted in Figure 8. The power outputs of each hydro and thermal unit with variation of load at a regular time interval are shown in Figure 9. The cost convergence

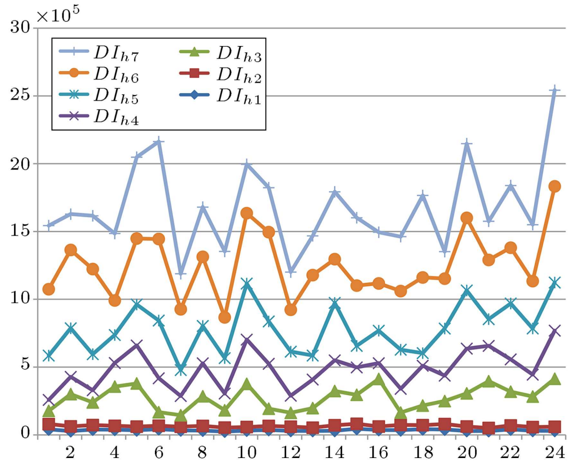

Figure 3. Hourly water discharges of different hydro plant for Test system I.

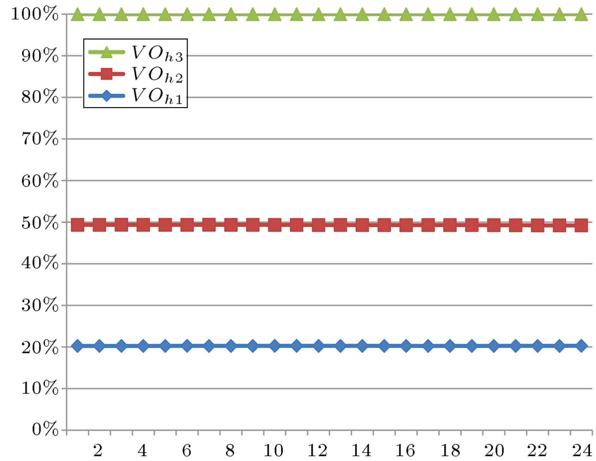

Figure 4. Variation of reservoir volume at different time intervals for Test system I.

characteristics achieved by GOA, GA, BBO, DE/BBO, and GWO methods are shown in Figure 10.

4.2.3. Test system III

It consists of a practical test system of India having seven hydro units and eight thermal units. Transmission loss is neglected. Input data are available in Tables A.1–A.4 in Appendix A. Table 9 shows the optimal hourly discharges of water of each hydro unit. Tables 10 and 11 describe the hydro and thermal power

Table 4. Performance analysis of different techniques taken after 50 trails.

Methods	Generation cost ($/h)			Time	No of hits to
	Max.	Min.	Average	(s)	minimum solution
GOA	**489036.3223**	**487142.7111**	**487218.45554**	**76**	**48**
GWO	489343.4197	488500.299	488567.74866	84	46
DE/BBO	490337.729	490083.6615	490103.9869	97	46
BBO	490448.649	490263.7445	490282.23496	105	45
GA	491405.6619	490853.5368	490941.87682	115	42

Table 5. Hourly hydro discharge obtained by Grasshopper Optimization Algorithm (GOA) algorithm for Test system-II.

Hour	Hydro discharges (m^3)						
	DI_{h1}	DI_{h2}	DI_{h3}	DI_{h4}	DI_{h5}	DI_{h6}	DI_{h7}
1	33590.63793	34959.95673	197797.335	167635.4973	335844.2266	583707.7866	214022.9464
2	25806.11954	25176.90201	218399.9328	342464.9957	436312.184	502540.882	486071.1822
3	24702.12652	41539.04342	250000.2443	112172.675	216509.6639	634886.744	360921.5856
4	29033.45065	26897.67625	137095.771	163550.7566	315096.8185	351961.1288	351869.24
5	34616.25317	42502.08782	60799.25463	214882.8593	99169.04448	359194.4357	313393.3658
6	36016.03536	36023.59317	78883.35491	255576.6494	454740.3366	487694.774	477488.3164
7	28219.25559	25266.04236	88762.49515	71042.69162	436141.696	525069.88	262440.1915
8	29789.23325	26299.79231	153944.1207	306518.4933	291803.1014	397998.3814	390452.0578
9	34422.06232	27675.59325	236280.7231	244970.5814	181341.1906	360764.9238	365473.5933
10	43046.88873	35782.93711	74617.4556	220387.9796	235585.4306	592509.9152	443514.113
11	30909.2605	37132.76981	231125.938	271137.1444	222229.05	643029.149	527912.7631
12	29697.7871	37829.60854	65935.30575	206543.2847	76083.27299	403868.3224	266184.1939
13	34232.72389	38534.37861	207234.5139	146789.9136	309741.6737	712559.9437	633188.1687
14	33091.55468	27014.20079	135942.355	218908.3398	453986.8172	530997.738	394681.4365
15	42197.5809	33297.52534	193727.8729	252409.077	409532.4293	518323.1673	619260.4656
16	28730.30157	30947.47649	259457.9055	319454.4099	260741.8701	353764.0812	338061.483
17	31815.09482	35079.78756	172496.3477	295092.1459	382050.5048	404871.6555	533501.2412
18	36667.77146	39544.43353	371264.2411	270057.3498	431162.8106	322300.3864	642754.2499
19	36404.45013	43359.94421	293712.6911	113604.4611	288574.5465	641444.8267	360644.3517
20	42228.42248	28086.10431	182411.8878	112323.3384	340109.3397	328630.4314	380130.9013
21	36656.5722	29210.84566	67036.2851	257047.2286	273668.8603	538560.212	585925.74
22	27372.43762	25624.76973	171584.599	153436.3154	467034.4592	520564.3892	400628.9643
23	33018.68788	27462.81856	340993.6014	170902.5889	379188.6932	460767.3047	661512.6209
24	25643.50209	25643.50209	284991.0846	284991.0846	284991.0846	206978.1845	206978.1845

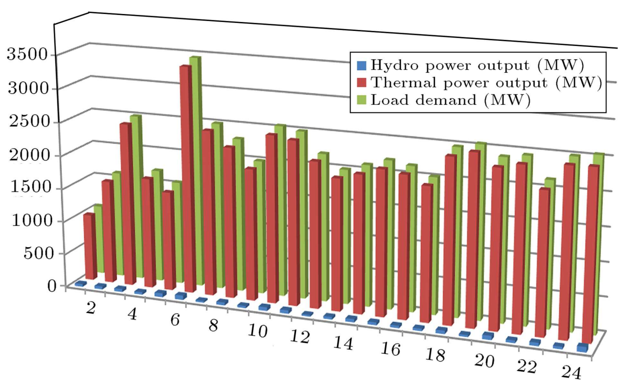

Figure 5. The hourly power generation of hydro and thermal plants with load demand for Test system I.

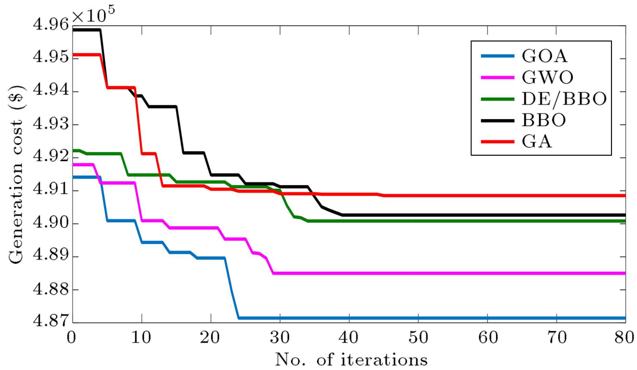

Figure 6. The convergence speed achieved by Grasshopper Optimization Algorithm (GOA), Genetic Algorithm (GA), BBO, DE/BBO, and Grey Wolf Optimizer (GWO) methods for Test system I.

generations achieved by GOA algorithm, respectively. The mean, best, and worst costs obtained by GOA and other existing optimization methods like GA, BBO, DE/BBO, and GWO are shown in Table 12. Figure 11 depicts the water discharges at different time intervals. Figure 12 shows the variations of reservoir volume for each time interval by GOA algorithm. The power outputs of each hydro and thermal unit with variation of load at a regular time interval are shown in Figure 13. The convergence speed achieved by GOA, GA, BBO, DE/ BBO, and GWO methods is shown in Figure 14.

5. Comparative study

5.1. Solution quality

The best, mean, and maximum costs obtained by GOA and other well-known methods like GA, BBO,

Table 6. Hydropower output for Test system II against minimum cost using Grasshopper Optimization Algorithm (GOA).

Hour	Hydro power output (MW)						
	HR_{p1}	HR_{p2}	HR_{p3}	HR_{p4}	HR_{p5}	HR_{p6}	HR_{p7}
1	0.6139	0.6840	5.2578	4.2320	9.9528	17.9680	1.5134
2	0.2154	0.1831	5.9585	10.1779	13.3697	14.3553	13.6222
3	0.1588	1.0209	7.0332	2.3457	5.8942	20.2460	8.0518
4	0.3806	0.2712	3.1933	4.0931	9.2471	7.6530	7.6489
5	0.6664	1.0702	0.5985	5.8389	1.9034	7.9749	5.9363
6	0.7381	0.7385	1.2135	7.2229	13.9964	13.6945	13.2402
7	0.3389	0.1877	1.5495	0.9469	13.3639	15.3581	3.6684
8	0.4193	0.2406	3.7663	8.9554	8.4549	9.7021	9.3662
9	0.6565	0.3111	6.5666	6.8621	4.6981	8.0448	8.2544
10	1.0981	0.7262	1.0684	6.0261	6.5430	18.3598	11.7280
11	0.4766	0.7953	6.3913	7.7521	6.0887	20.6084	15.4846
12	0.4146	0.8310	0.7732	5.5552	1.1183	9.9634	3.8351
13	0.6468	0.8670	5.5787	3.5230	9.0650	23.7032	20.1704
14	0.5884	0.2772	3.1541	5.9758	13.9708	15.6219	9.5545
15	1.0546	0.5989	5.1194	7.1151	12.4589	15.0578	19.5505
16	0.3651	0.4786	7.3549	9.3953	7.3985	7.7332	7.0343
17	0.5230	0.6902	4.3973	8.5668	11.5242	10.0080	15.7333
18	0.7715	0.9188	11.1574	7.7154	13.1945	6.3328	20.5962
19	0.7580	1.1141	8.5199	2.3944	8.3451	20.5379	8.0395
20	1.0562	0.3321	4.7345	2.3508	10.0978	6.6145	8.9068
21	0.7709	0.3897	0.8106	7.2729	7.8382	15.9585	18.0668
22	0.2955	0.2061	4.3663	3.7491	14.4145	15.1575	9.8192
23	0.5846	0.3002	10.1279	4.3431	11.4269	12.4960	21.4311
24	0.2070	0.2070	8.2232	8.2232	8.2232	1.1998	1.1998

Table 7. Thermal power output for Test system II against minimum cost using Grasshopper Optimization Algorithm (GOA).

Hour	Thermal power output (MW)			
	TH_{p1}	TH_{p2}	TH_{p3}	TH_{p4}
1	331.5562351	355.5824522	199.1407687	123.4986659
2	487.8289462	362.2402057	271.8077616	420.2409792
3	764.2026314	585.5493386	426.0907992	679.4065994
4	587.3510344	443.304046	209.0245329	427.8331322
5	584.3799821	358.9961824	208.380749	374.2543966
6	1560.845923	600.4355873	498.1935373	739.6808604
7	1590.698642	627.9307705	499.4284401	746.5288134
8	666.0959424	589.375528	425.5218599	578.1017655
9	2117.19067	587.7268128	499.7613932	759.9274164
10	1663.663828	620.721699	495.4167718	724.6481297
11	1685.068788	608.6787928	423.7623485	724.8930567
12	2293.331546	629.9720884	498.408751	755.7969251
13	2119.120912	597.299512	497.1736925	722.8516142
14	2163.379694	627.7256077	499.8901828	759.8618974
15	2252.597894	629.9992463	498.4203095	758.0273775
16	2226.724755	629.7731833	498.8178353	754.9242694
17	2117.702719	627.9852436	497.0250669	725.8440927
18	1945.066927	619.291711	498.9349423	756.0199187
19	1758.112509	598.059681	497.1734536	746.9454936
20	1498.149164	617.9586667	498.2077264	751.5916483
21	1639.412505	593.9741893	490.4597061	675.0460993
22	1277.529932	589.4744581	497.8355926	727.1517813
23	1034.692455	629.4923789	499.7076326	725.3977435
24	1023.34016	607.9474022	465.3570154	725.8720295

Table 8. Performance analysis of different techniques taken after 50 trails.

Methods	Generation cost ($/h)			Time (s)	No of hits to minimum solution
	Max.	Min.	Average		
GOA	**637490.2645**	**637275.9866**	**637288.84328**	**96**	**47**
GWO	637659.1476	637494.6423	637507.80272	103	46
DE/BBO	637946.4291	637659.1476	637687.87576	107	45
BBO	638032.6965	637751.256	637779.40004	111	45
GA	639039.6396	638135.6659	638262.22222	121	43

Table 9. Hourly hydro discharge obtained by Grasshopper Optimization Algorithm (GOA) algorithm for Test system III.

Hour	Hydro discharges $\times 10^4$ (m^3)						
	DI_{h1}	DI_{h2}	DI_{h3}	DI_{h4}	DI_{h5}	DI_{h6}	DI_{h7}
1	3.5368211650	3.1763728250	29.262475750	38.30332297	19.29122459	67.00416046	44.72746009
2	3.6976109460	2.7794389810	38.085137020	7.882892833	32.57854105	60.09293966	19.42362478
3	2.2816850280	3.6756712980	39.485973000	27.75753121	10.29109875	60.62033437	28.71988315
4	2.1709859760	2.9245240720	36.075354060	10.26317213	8.445541715	30.32660957	54.4154159
5	3.4734322470	3.3566796890	13.793752490	25.56933946	45.92541002	23.34654318	59.8759611
6	3.2259009710	2.2119079650	33.632832360	32.29365557	11.24257464	21.37857991	45.2837661
7	4.3821078370	4.3494269310	7.183928903	30.47729155	35.31032668	40.61766805	54.68712315
8	2.2589909170	3.0576653800	29.534732250	5.633396442	27.59728204	30.06370152	28.89916402
9	2.4443218940	2.4391964530	22.906296490	18.75336609	33.01863808	69.66799335	46.63854535
10	2.9568352770	3.7195960310	37.047680140	21.86465339	28.24902173	50.367009	60.69541845
11	3.4078772150	4.0652190180	38.678428220	25.40126712	6.315070488	54.85852694	36.95667551
12	3.9110831480	2.5238307130	23.263800670	5.919546187	20.82587812	41.18530017	22.03537932
13	4.2740941080	3.8723816960	35.389249920	35.98777484	16.90872133	20.80049455	53.86007378
14	4.1183008190	3.1362169080	6.708170680	22.85315054	16.27184379	28.28534144	27.80748501
15	3.0165848400	2.2296545040	7.469863973	21.68019224	34.73894743	71.38885664	18.12890624
16	3.4016508450	3.2086292880	6.032220216	27.26944929	8.433135705	74.16000000	67.68749854
17	4.4346357930	3.6251419470	21.303268390	34.20608508	9.592988643	42.14047974	49.23619612
18	2.1908849570	3.0010776350	19.029953670	24.88983595	38.13043806	58.30840265	47.94846527
19	4.2896153180	2.6177255510	36.821535530	8.473883987	47.47740258	51.30050953	52.34709442
20	3.6502778430	2.8706619150	14.419176890	14.32501509	11.29831733	33.66277424	72.07566343
21	2.2899633980	3.6366166510	10.181515320	18.86592357	36.53061576	35.48639422	40.78413521
22	2.3397321280	3.6280992130	27.007145980	32.64016413	41.62873587	35.86225185	44.69641044
23	2.6845184380	3.5401750180	37.468298580	26.32772287	10.27747272	24.90933657	64.26298172
24	4.3980896060	4.3980896060	26.497548620	26.49754862	26.49754862	46.48623262	46.48623262

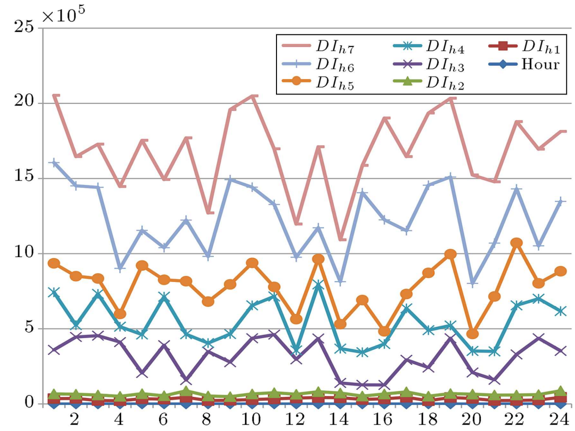

Figure 7. Hourly water discharges of different hydro plants for Test system II.

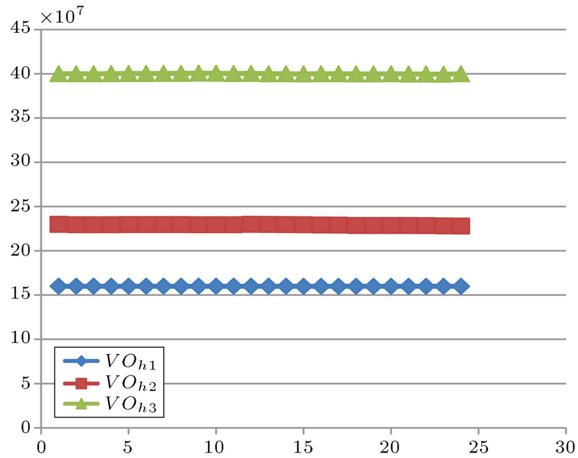

Figure 8. Variation in reservoir volumes at different time intervals for Test system II.

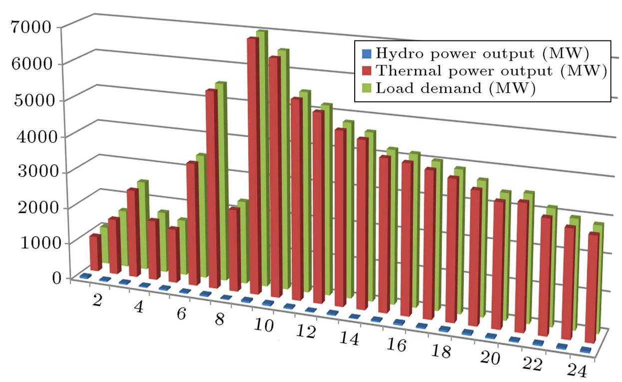

Figure 9. The hourly power generation of hydro and thermal plants with load demand for Test system II.

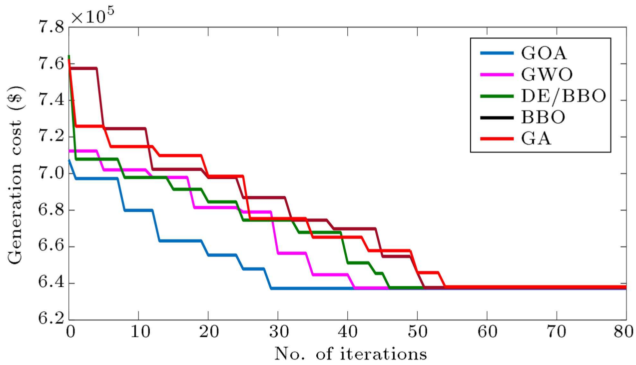

Figure 10. The convergence speed achieved by Grasshopper Optimization Algorithm (GOA), Genetic Algorithm (GA), BBO, DE/BBO, and Grey Wolf Optimizer (GWO) methods for Test system II.

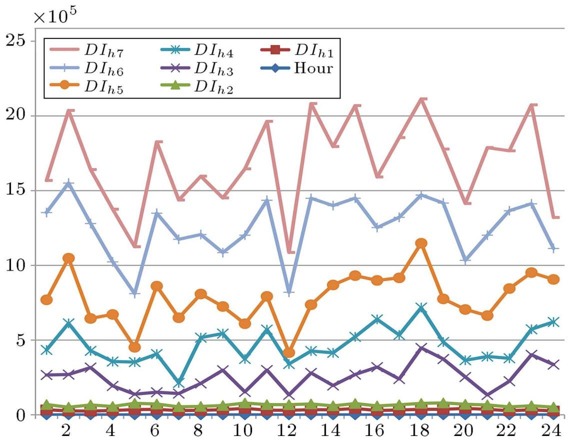

Figure 11. Hourly water discharges of different hydro plants for Test system III.

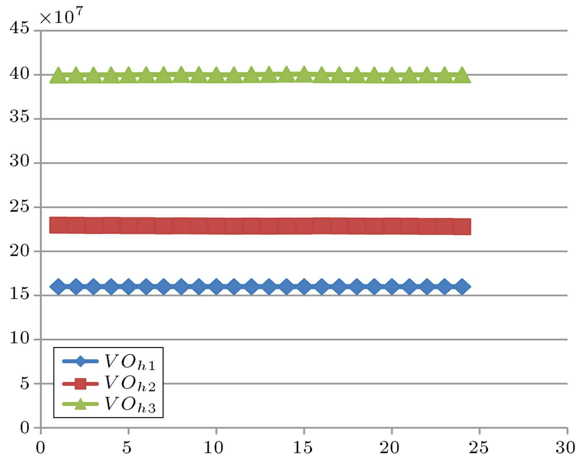

Figure 12. Variation of reservoir volume at different time intervals for Test system III.

DE/BBO, and GWO are shown in Tables 4, 8, and 12, respectively. From these tables, it is clear that the cost obtained by GOA method is lower than the other well-known methods. For example, in Test system I, the cost obtained by GOA technique is 487142.7111 $/h, whereas the costs obtained by GA, BBO, DE/BBO, and GWO are 490853.5368 $/h, 490263.7445 $/h, 490083.6615 $/h, and 488500.299 $/h, respectively. Same results were observed for the Test systems II and III. Therefore, these results show the capability of GOA

Table 10. Hydropower output for Test system III against minimum cost using Grasshopper Optimization Algorithm (GOA).

Hour	Hydro power output (MW)						
	HR_{p1}	HR_{p2}	HR_{p3}	HR_{p4}	HR_{p5}	HR_{p6}	HR_{p7}
1	0.7049	0.5204	8.4829	11.5577	5.0916	21.8108	11.8954
2	0.7873	0.3172	11.4835	1.2117	9.6107	18.7346	0.6327
3	0.0623	0.7760	11.9599	7.9710	2.0307	18.9693	4.7704
4	0.0056	0.3914	10.7999	2.0212	1.4030	5.4856	16.2075
5	0.6725	0.6127	3.2220	7.2268	14.1499	2.3787	18.6380
6	0.5457	0.0266	9.9692	9.5138	2.3543	1.5028	12.1430
7	1.1377	1.1210	0.9740	8.8960	10.5397	10.0661	16.3284
8	0.0507	0.4596	8.5755	0.4466	7.9165	5.3686	4.8502
9	0.1456	0.1429	6.3211	4.9087	9.7603	22.9964	12.7460
10	0.4080	0.7985	11.1306	5.9669	8.1382	14.4056	19.0027
11	0.6389	0.9755	11.6852	7.1697	0.6785	16.4047	8.4366
12	0.8966	0.1863	6.4427	0.5439	5.6136	10.3188	1.7951
13	1.0824	0.8767	10.5666	10.7701	4.2814	1.2455	15.9603
14	1.0027	0.4998	0.8121	6.3031	4.0648	4.5770	4.3643
15	0.4386	0.0357	1.0712	5.9041	10.3454	23.7624	0.0564
16	0.6357	0.5369	0.5823	7.8050	1.3988	24.9958	22.1149
17	1.1646	0.7502	5.7759	10.1642	1.7933	10.7439	13.9022
18	0.0158	0.4306	5.0028	6.9957	11.4989	17.9403	13.3291
19	1.0904	0.2344	11.0537	1.4127	14.6778	14.8211	15.2869
20	0.7630	0.3639	3.4347	3.4026	2.3733	6.9705	24.0681
21	0.0665	0.7560	1.9934	4.9470	10.9548	7.7822	10.1402
22	0.0920	0.7517	7.7158	9.6316	12.6886	7.9495	11.8816
23	0.2686	0.7066	11.2737	7.4848	2.0261	3.0743	20.5907
24	1.1459	1.1459	7.5425	7.5425	7.5425	12.6782	12.6782

method to produce a quality solution in a consistent manner.

5.2. Robustness

The program was run for 50 trials in order to check the robustness of this GOA algorithm. The success rates of this GOA algorithm and other existing methods like GA, BBO, DE/BBO, and GWO are presented in Tables 4, 8, and 12, respectively. It was found that out of 50 trails, GOA hit the best solution 48 times for Test system I, 47 times for Test system II, and 50 times for Test system III. Thus, the success rate achieved by GOA is 96%, 94%, and 100%, respectively. In Test system I, out of 50 trails, GA, BBO, DE/BBO, and GWO hit the best solution 42 times, 45 times, 46 times, and 46 times, respectively. In Test case II, the success rates achieved by GA, BBO, DE/BBO, and GWO are 84%, 88%, 90%, and 92%, respectively. For Test system II, the success rates achieved by GA, BBO, DE/BBO, and GWO are 84%, 90%, 92%, and 92%, respectively.

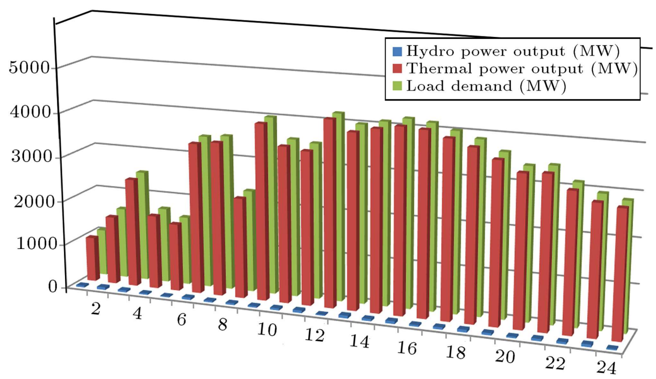

Figure 13. The hourly power generation of hydro and thermal plants with load demand for Test system III.

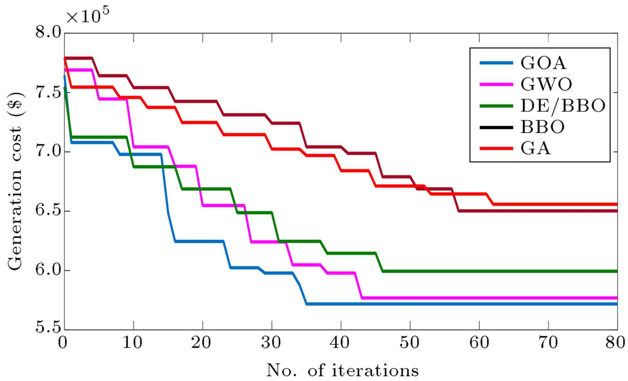

Figure 14. The convergence speed achieved by Grasshopper Optimization Algorithm (GOA), Genetic Algorithm (GA), BBO, DE/BBO, and Grey Wolf Optimizer (GWO) methods for the Test system III.

Table 11. Thermal power output for Test system III against minimum cost using Grasshopper Optimization Algorithm (GOA).

	Thermal power output (MW)							
Hour	$TH_{p1} \times 10^3$	TH_{p2}	TH_{p3}	TH_{p4}	$TH_{p5} \times 10^3$	TH_{p6}	$TH_{p7} \times 10^3$	TH_{p8}
1	0.2343	134.3742	50.2022	123.4190	0.1001	69.4255	0.1580	120.2311
2	0.2358	252.2844	296.0397	221.5022	0.1067	167.9139	0.1561	120.8922
3	0.4179	585.1301	297.1132	380.3054	0.2981	206.2271	0.1479	120.7977
4	0.2340	213.4500	146.8695	178.7985	0.2127	209.2651	0.3485	120.1005
5	0.3190	358.6061	126.4816	132.9660	0.2106	73.2203	0.1597	122.5848
6	0.5333	512.2726	296.6516	605.1446	0.6985	185.4223	0.4557	126.9647
7	1.3114	629.8930	499.9453	742.0415	0.9476	209.9568	0.9899	120.1079
8	0.3454	494.7274	203.0334	335.4770	0.3082	177.5198	0.2866	121.3642
9	2.3400	630.0000	500.0000	760.0000	1.0000	210.0000	1.0000	502.9790
10	2.2835	629.9980	499.9601	759.9879	0.9976	209.9979	0.9891	120.0118
11	1.2472	629.9930	499.5426	759.9074	0.9991	209.1568	0.9889	120.1772
12	1.0422	618.9608	499.0553	759.9557	0.9977	207.5712	0.9285	120.2426
13	0.9572	594.6443	498.0779	727.0368	0.9517	209.9996	0.6957	120.8315
14	0.9570	628.3121	499.9847	733.7249	0.8013	170.1067	0.6642	123.7046
15	0.7448	591.0216	497.2501	717.3184	0.6401	209.5537	0.6335	124.7802
16	0.6823	626.5212	495.7070	708.7341	0.7854	209.9665	0.4546	128.6981
17	0.7717	590.4466	499.9948	722.8798	0.5944	209.8070	0.4630	123.5245
18	0.6777	585.3046	492.3081	629.4499	0.6682	197.1005	0.4536	121.1592
19	0.6900	566.8618	428.3938	618.9922	0.6458	174.2474	0.3432	123.8094
20	0.5883	627.7235	356.0904	441.4742	0.6098	208.9371	0.4033	122.9804
21	0.6750	596.7715	498.8828	567.5745	0.3996	160.1511	0.3925	122.9196
22	0.4905	589.6218	499.9925	437.3202	0.4933	169.7698	0.2852	123.5080
23	0.5986	592.7626	335.2046	381.8242	0.4490	154.5224	0.2653	127.3867
24	0.5033	619.0501	290.4074	416.7887	0.3047	209.8466	0.3339	121.8389

Table 12. Performance analysis of different techniques taken after 50 trails.

Methods	Generation cost ($/h)			Time	No of hits to
	Max.	Min.	Average	(s)	minimum solution
GOA	**571827.2513**	**571827.2513**	**571827.2513**	**110**	**50**
GWO	581496.0532	576893.669	577445.955	116	46
DE/BBO	621234.541	599396.832	602890.865	121	45
BBO	650898.569	650250.061	650327.881	127	44
GA	659735.086	655835.563	656459.486	135	42

Therefore, it is observed that the consistency of GOA method is better than other soft computing techniques.

5.3. Computational efficiency

The time taken for GOA algorithm to reach the best solution is shorter than those for other methods such as GA, BBO, DE/BBO, and GWO. The simulation time obtained by GOA, GA, BBO, DE/BBO, and GWO algorithm is depicted in Table 4, 8, and 12, respectively. From Table 4, it is realized that the time obtained by GOA method is 76 seconds, whereas the times obtained by GA, BBO, DE/BBO, and GWO are 115, 108, 97, and 84 seconds, respectively. The similar results are found when this GOA method is applied to the other two test systems. Therefore, it is clear that the computational efficiency of GOA algorithm is higher than that of other popular soft techniques.

It is found that the total number of iterations required to reach the best solution is less than other algorithms like GA, BBO, DE/BBO, and GWO. In Test system I, the iterations required to achieve the best solution is less in case of GOA technique among other popular soft computing methods. From Figure 6, it is seen that the number of iterations required to attain the best solution is only 25, whereas the iterations required to achieve the best result is 46 for GA, 40 for BBO, 35 for DE/BBO, and 30 for GWO. In the test case II, the iterations required to reach the

Table 13. Effect of intensity of attraction (a) on Grasshopper Optimization Algorithm (GOA).

Attraction length (l_a)	Intensity of attraction (a)	Test system I	Test system II	Test system III
$l_a = 1.5$	$a = 0.1$	491432.2008	652147.2369	602147.2813
	$a = 0.2$	490923.1237	646214.3087	594127.3615
	$a = 0.3$	489614.3389	639874.4123	587521.3914
	$a = 0.4$	489213.2591	638814.3693	587323.6614
	$\boldsymbol{a = 0.5}$	**487142.7111**	**637275.9866**	**571827.2513**
	$a = 0.6$	487812.3398	642141.0236	587412.3258
	$a = 0.7$	487423.1103	638741.1169	589217.3887
	$a = 0.8$	487949.3614	649871.2522	593742.6985
	$a = 0.9$	490021.3698	638821.4569	578798.3244
	$a = 1.0$	490012.7456	637989.2147	589465.2746

Table 14. Effect of population size.

Swarm size	Test system I	Test system II	Test system III
5	491774.2314	665487.3314	614756.5813
10	490914.3229	651423.3685	601232.4789
20	489561.7698	641124.1235	583678.3793
30	**487142.7111**	**637275.9866**	**571827.2513**
40	489652.1147	648793.2014	593214.3698
50	490096.1299	654141.8745	592214.3621
60	491125.9813	659785.3477	601452.3049

best result is 30 for GOA, 55 for GA, 52 for BBO, 47 for DE/BBO, and 42 for GWO. In the test case III, the iterations required to reach the best result is 37 for GOA, 63 for GA, 58 for BBO, 47 for DE/BBO, and 44 for GWO. Therefore, the convergence rate of GOA technique is found to be faster than that of other optimization techniques.

5.4. Parameter tuning and effect of population size

In case of the optimization process, appropriate tuning of control parameter is a very crucial task. In this paper, two control parameters including attraction length (l_a) and intensity of attraction (a) are chosen to demonstrate the performance of the GOA method. Table 13 describes the results obtained by GOA method according to the variation in the intensity of attraction (a). It was found that the result was obtained with $l_a = 1.5$ and $a = 0.5$ at best for all test systems. The effect of swarm size (population size) was observed for running GOA algorithm for 50 individual trails with swarm sizes of 5, 10, 20, 30, 40, 50, and 60. The simulation results obtained by GOA technique for different swarm sizes are depicted in Table 14. It was observed that GOA yielded the best result for all test systems when the swarm size 30 is chosen. In addition, it was found that the performance of GOA method did not improve when swarm size was set above or below 30.

5.5. Statistical analysis

A variety of statistical methods [59,60] have so far been in use to conduct a comparative analysis of algorithms. In the present paper, comparative analyses of performances of GOA algorithms were carried out statistically through Friedman test and Quade test [36,59,60]. For performing Friedman test and Quade test, a null hypothesis (H_0) was employed. H_0 indicates that there is no difference between the methods in terms of performance in comparison [36], and an alternative hypothesis (H_1) signifying difference in their performances needs to be defined. A 5% significance level is fixed. The statistical analyses of the results obtained by using GOA, GWO, DE/BBO, BBO, and GA algorithms are presented in Table 15. The F-statistic (Chi-Square) value, given in Table 15,

Table 15. Ranks achieved by Friedman and Quade tests for Test systems I, II, and III. The statistical computed and related p-values are also shown.

Friedman test						Quade test					
Test systems	GOA	GWO	DE/BBO	BBO	GA	Test systems	GOA	GWO	DE/BBO	BBO	GA
	1	2	3	4	5	Test system I	-4	-2	0	2	4
Test system I	1	2	3	4	5	Test system II	-2	-1	0	1	2
Test system II	1	2	3	4	5	Test system III	-6	-3	0	36	
Statistic			12			Statistic			12		
p-value			0.0174			p-value			0.0018		

Table 16. Average errors obtained in Test systems I and II.

Test systems	GOA	GWO	DE/BBO	BBO	GA
Test system I	75.74444	1425.03756	2961.2758	3139.52386	3799.16572
Test system II	12.85668	231.81612	411.88916	503.41344	986.23562
Test system III	0	5618.7037	31063.6137	78500.6297	84632.2347

is 12 and Q-statistic value is 12. Thus, the F-statistic value and Q-statistic value are found to be greater than their corresponding critical values in both of the above cases. The p-values procured from Friedman test and Quade test turned out to be lower than those at a 5% significance level. This leads to the rejection of the null hypothesis which, in turn, signifies a remarkable difference in the performance between the algorithms. Table 16 exhibits the average errors of various techniques.

The calculation of average errors was carried out in the following steps: First, the least value among all the algorithms for each test system was found. Next, the least value was subtracted from the mean value obtained by each algorithm. Finally, all algorithms were arranged rank-wise based on the value of average error. Thus, the algorithms were ranked based on the average errors, as shown in Table 15. As seen from the tables, GOA algorithm attains the lowest rank, which indicates the better performance of GOA. Thus, it may be concluded that GOA algorithm gives a better quality solution in comparison to other recently developed optimization techniques.

6. Conclusion

In this paper, Grasshopper Optimization Algorithm (GOA) [55] was used for solving the short-term Hydrothermal Scheduling (HTS) problem. The variable nature of water transportation delay [58] was introduced here. The hydropower generation was calculated based on the volume segment of water. To examine the feasibility, computational efficiency, and consistency of GOA algorithm, two different test systems were considered. The results obtained by GOA method were compared with those by other optimization methods such as Grey Wolf Optimizer (GWO), DE/BBO, BBO, and Genetic Algorithm (GA). The proposed optimization technique was found superior to other well-established techniques of optimization in terms of computational time, consistency, and solution quality. Therefore, this technique may be applied to find the solution to different complex optimization problems.

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Appendix

Input data are shown in Tables A.1 to A.4.

Table A.1. Volume limits of reservoir.

Station	Capacity (MW)	$VO_h^{\max}$ (10^6m^3)	$VO_h^{\min}$ (10^6m^3)	VO_h^{begin} (10^6m^3)	VO_h^{end} (10^6m^3)	$DI_h^{\max}$ (10^4m^3)
1	63.2	566	220	230	228	7.2
2	80	1475.65	350	400	400	127.4
3	4	394	150	160	159.9	5.76

Table A.2. Fuel cost coefficients.

Unit no.	*A*	*B*	*C*	*E*	*F*
1	0.005	1.89	150	300	0.035
2	0.0055	2	115	200	0.042
3	0.006	3.5	40	200	0.042
4	0.005	3.15	122	150	0.063
5	0.005	3.05	125	150	0.063
6	0.007	2.75	120	150	0.063
7	0.007	3.45	70	200	0.053
8	0.07	3.45	70	150	0.063

Table A.3. Maximum and minimum generation limits of thermal units.

Unit no	$TH_p^{\max}$ (MW)	$TH_p^{\min}$ (MW)
1	2340	234
2	630	63
3	500	50
4	760	76
5	1000	100
6	210	21
7	1000	100
8	1200	120

Table A.4. 24-hour load demand.

Hour	Load demand (Test system I)	Load demand (Test system II)	Load demand (Test system III)
1	1050	1050	1050
2	1600	1600	1600
3	2500	2500	2500
4	1700	1700	1700
5	1550	1550	1550
6	3450	3450	3450
7	2500	5500	3500
8	2300	2300	2300
9	2000	7000	4000
10	2550	6550	3550
11	2500	5500	3500
12	2200	5200	4200
13	2000	4800	4000
14	2100	4600	4100
15	2200	4200	4200
16	2150	4150	4150
17	2020	4020	4020
18	2480	3880	3880
19	2550	3650	3650
20	2400	3400	3400
21	2450	3450	3450
22	2140	3140	3140
23	2500	2950	2950
24	2550	2850	2850

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