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A grasshopper optimization algorithm for optimal short-term hydrothermal scheduling

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ABSTRACT

The optimal generation for short-term hydrothermal scheduling (OGStHS) with the deliberation of various purposes is a complex non-linear constrained optimization problem. There exist numerous constraints, which make the OGStHS optimization problem more complicated. The considered constraints for this problem are mostly related to energy performance, operational conditions, water, and power infrastructure. All these constraints would generally influence the cost of fuel. In this study, a multi-objective optimization form of OGStHS is suggested to estimate the minimum cost of fuel, which mainly influences industrial operation. The water transfer delays among multi-related reservoirs and the thermal plants' valve-point influences are considered for the accurate formulation of the OGStHS problem. Meantime, a grasshopper optimization algorithm (GOA) is performed to handle the OGStHS problem by getting optimized for both objectives concurrently. A modern approach is shown in this study to get a solution to the OGStHS problem. Furthermore, to deal with the complex restraints efficiently, modern heuristic restriction treatment processes with no drawback impact frames have been offered in this study. Two hydrothermal power systems have illustrated the suggested GOA technique's utility and performance. Compared with other available approaches, the analytical results are admitted that GOA can provide a better understanding by decreasing fuel cost and emission concurrently.

1. Introduction

The short-term hydrothermal scheduling (StHS) is the most concerning problem for ensuring an interrelated power system's optimal operation. In the hydrothermal power system (HPS), the StHS problem refers to the optimal generation for short-term hydrothermal scheduling (OGStHS). This indicates locating the optimal volume of water discharges of hydro plants and thermal plants' power resources during a schedule extent to minimize the entire energy production cost while performing different hydraulic constraints and operations limitations. It is evident that, in an interrelated HPS, hydropower plant's operation cost has not been as significant as thermal plants (Kumar and Mohan, 2011; Lu et al., 2011; Hammid et al., 2018a). Therefore, the OGStHS problem's purpose was to minimize the entire cost of the thermal plant's fuel input while performing complex environmental constraints and operations limitations. These include the balance of load and water dynamics and constraints of reservoir storage volumes and water discharge limitations and production capacity limitations. Regularly, in HPS, the fuel cost function for an individual thermal unit is described nearly as a quadratic function. The energy production for an individual hydro unit has been defined by stream and reservoirs storages of water concurrently. Therefore, the probable water resources available for energy production through hydropower turbines at every period of the schedule extent based on the prior scheduling decision. The dynamic combination generally sets these decisions among the system's operators based on the features during the schedule extent. Analytically, the OGStHS problem may be classified as an extensive, robust, nonlinear, and non-convex optimization problem with different complex constraints, determining the final

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decision optimal schedule with system challenges efficiently (Lu et al., 2010; Hammid et al., 2018b; Hammid and Sulaiman, 2018).

Over the years, several conventional approaches have been suggested to make a solution to the OGStHS problem. The conventional approaches are mostly mathematical techniques such include linear programming (LP) (Piekutowski et al., 1993), decomposition method (Mohan et al., 1992), progressive optimality algorithm (POA) (Turgeon, 1981), dynamic programming (DP) (Tang and Luh, 1995; Chang et al., 1990), Lagrange relaxation-based algorithms (Guan et al., 1995; Salam et al., 1998). However, most of these studies do not have the capability to determine optimal scheduling decisions due to their shortcomings. While the suffering, drawback, and inability of the above highlighted, conventional approaches are briefly explained in ref. Lu et al. (2010).

Several recent heuristics stochastic search techniques include genetic algorithm (GA) (Orero and Irving, 1998; Yuan et al., 2002), evolutionary programming (Sinha et al., 2003; Basu, 2004), simulated annealing (Wong and Wong, 1994), particle swarm optimization (PSO) (Mandal et al., 2008; Hota et al., 2009; Zhang et al., 2016), differential evolution (DE) algorithm (Lakshminarasimman and Subramanian, 2008; Mandal and Chakraborty, 2008), artificial bee colony algorithm (Tehzeeb ul et al., 2020), Gray Wolf Optimization (Sharma et al., 2020), mixed-integer formulation of the LP (Jian et al., 2019), An adaptive cuckoo search algorithm (Nguyen et al., 2018), Teaching learning-based optimization (TLBO) (Roy, 2013), and Improved harmony search algorithm (Nazari-Heris et al., 2018). All these algorithms can show their ability to find out the solution to the OGStHS problem without limitation on the problem's non-convex aspect due to their robust capability for searching. Nonetheless, rather than supplying the final decision of the globe optimal schedule, all the above-highlighted techniques can give a suboptimal solution for obtaining the restricted local optimal points since their shortcomings.

The No Free Lunch hypothesis in the optimization field (Wolpert and Macready, 1997) says that there is not and will not be an optimization technique to solve entire optimization problems. Consequently, a recent strategy based on the grasshopper optimization algorithm (GOA) can solve the current subproblem on a collection of problems. The GOA, which appeared recently, may have the ability to determine the final decisions more reliably with or without justification when comparing the current techniques. Saremi et al. (2017) and Aljarah et al. (2018) proved that the approach mentioned above exceeded the extreme of the existing techniques on problems include system challenges with a large-scale amount of local solutions (multi-modal). This modification on the engagement of the approach in this cited study aims to obtain its recent operators' utility to make a solution and be adequately handled by the OGStHS optimization problem's constraints. Lastly, from the parameters of various constraints of the OGStHS problem, the procedures governing constraints related to the heuristic approaches without utilizing any discipline features are suggested for GOA to handle the problem's constraints.

Hence, in this study, to prove the suggested approach's probability and good performance, i.e., GOA has been employed to make a solution for the OGStHS problem of two different hydrothermal systems. The article is structured in six different sections; in Section 2, the problem formulation is briefly presented. Section 3 presents the GOA use for the OGStHS problem. In Section 4, the optimization's execution procedure is discussed, and results are briefly explained along with the literature comparison in Section 5. Finally, the conclusions were drawn in Section 6.

2. Problem formulation

The optimal generation for OGStHS with the deliberation of various purposes is a complex non-linear, constrained optimization problem.

Hence, the objective function and the associated constraints are formulated, and the details are presented in the below subsections.

2.1. Objective function

The principal goal of the OGStHS problem is getting minimized the gross cost of fuel (F) while performing different types of constraints. The objective function for generating units (N_s) with interval times (T) is expressed by Eq. (1) (Das and Bhattacharya, 2018):

$$F = min \sum_{t=1}^{T} \sum_{i=1}^{Ns} f_i \left(P_{si}^t\right) \tag{1}$$

where the energy production of the ith thermal plant is (P_{si}^t) at a specific period of time (t). The cost of fuel for the ith unit is (($f_i(P_{si})$) at the production of the P_{si}^t, which is determined by Eq. (2):

$$f_i(P_{si}) = x_i + (y_i \cdot P_{si}) + (z_i \cdot P_{si}^2) + a_i sin\left(b_i \cdot \left(P_{si,min} - Psi\right)\right) \tag{2}$$

Moreover, in the real world HPS, there will be an apparent rise in the thermal fuel price, which would influence the overall fuel cost curve. Besides, the wire design also affects when the valve's steam entry begins to start. The apparent loss of fuel rise has been expressed as valve point influences. The curve of fuel cost of the thermal plant with the main idea of valve-point influences is quite exact to the equation described in Eq. (2). where x_i, y_i, and z_i are the coefficients of cost for generator i. Also, a_i, b_i are the valve-point influences coefficients of the generator i. $P_{si,min}$ is the minimum power generation limit of generator i.

2.2. Constraints

The associated constraints of the OGStHS problem are briefly described in the below sections (Das et al., 2018; Hammid et al., 2017):

2.2.1. Generation of hydropower

For the jth hydro plant at a specific period of time (t), power generation is determined by Eq. (3):

$$P_{hj}^t = z_{1j}\left(V_{hj}^t\right)^2 + z_{2j}\left(Q_{hj}^t\right)^2 + z_{3j}\left(V_{hj}^t Q_{hj}^t\right)^2 + z_{4j}V_{hj}^t + z_{5j}Q_{hj}^t + z_{6j} \tag{3}$$

where the power production of the jth hydro plant is (P_{hj}^t) at a specific period of time (t). $z_{1j}, z_{2j}, z_{3j}, z_{4j}, z_{5j}$, and z_{6j} are the coefficients. V_{hj}^t is the volume of the jth hydro plant at a specific period of time (t). Q_{hj}^t is the water release of the jth hydro plant at a specific period of time (t).

2.2.2. Balance constraints of real energy

The constraint related to real energy is given by Eq. (4):

$$\sum_{i=1}^{Ns} P_{si}^t + \sum_{j=1}^{Nh} P_{hj}^t = P_D^t + P_{lossj} \tag{4}$$

where the gross demand for the load is (P_D^t) at a specific period of time (t). The number of thermal and hydro plants is (N_s) and (N_h), respectively.

2.2.3. Operating limitations of thermal plant

The constraint related to the operating limits of the thermal plant is given by Eq. (5):

$$P_{si,min} \leq P_{si}^{t} \leq P_{si,max}$$
$$i = 1, 2, \ldots, N_s$$
$$t = 1, 2, \ldots, T \tag{5}$$

where the minimum and the maximum energy production of the ith thermal plant are $P_{si,min}$ and $P_{si,max}$ respectively.

2.2.4. Operating limitations of the hydro plant

The constraint related to the operating limits of the hydro plant is given by Eq. (6):

$$P_{hj,min} \leq P_{hj}^{t} \leq P_{hj,max}$$
$$j = 1, 2, \ldots, N_h$$
$$t = 1, 2, \ldots, T \tag{6}$$

where the minimum and the maximum energy production of the jth hydro plant are $P_{hj,min}$ and $P_{hj,max}$ respectively.

2.2.5. Limitations of water release for hydro plants

The constraint related to the limitations of water release for the hydro plant is given by Eq. (7):

$$Q_{hj,min} \leq Q_{hj}^{t} \leq Q_{hj,max}$$
$$j = 1, 2, \ldots, N_h$$
$$t = 1, 2, \ldots, T \tag{7}$$

where the minimum and the maximum water release of the jth hydro plant are $Q_{hj,min}$ and $Q_{hj,max}$ respectively.

2.2.6. Volumes limitations of reservoir storage

The constraint related to the limitations of the volume of reservoir storage is given by Eq. (8):

$$V_{hj,min} \leq V_{hj}^{t} \leq V_{hj,max}$$
$$j = 1, 2, \ldots, N_h$$
$$t = 1, 2, \ldots, T \tag{8}$$

where the minimum and the maximum volumes of the jth hydro plant are $V_{hj,min}$ and $V_{hj,max}$ respectively.

2.2.7. Balance of water dynamic

The constraint related to the balance of water dynamic is given by Eq. (9):

$$V_{hj}^{t} = V_{hj}^{t-1} + I_{hj}^{t} - Q_{hj}^{t} + \sum_{m=1}^{Nj} Q_{hm}^{t-\lambda_{mj}} \tag{9}$$

where the entire of upstream hydro plants straight overhead the jth hydro plant is (N_j).

2.2.8. Initial and final reservoir storage

The constraint related to the balance of water dynamic is given by Eq. (10):

$$V_{hj}^{0} = V_{hj,ini}; \mathrm{V}_{hj}^{T} = V_{hj,fin} \tag{10}$$

where the initial and final reservoir storage of the jth hydro plant is $V_{hj,ini}$ and $V_{hj,fin}$ respectively.

3. Grasshopper optimization algorithm for hydrothermal scheduling

The GOA algorithm has been suggested to address the problem of OGStHS, and the more detailed information on how it is applied can be found in refs. Saremi et al. (2017) and Aljarah et al. (2018). This algorithm simulates the normal behavior of grasshopper's swarms. The trajectory of jumping off for every grasshopper in a specific swarm is influenced by three factors: group interaction (G_i), gravity (G_r), and wind effect horizontally (W_e). In the GOA algorithm, group interaction is the principal procedure of exploration determined according to Eq. (11):

$$G_i = \sum_{j=1, j\neq i}^{N} G\left(l_{ij}\right)\hat{l}_{ij} \tag{11}$$

where the length between ith and jth grasshopper is (l_{ij}) then it has been determined as $l_{ij} = x_j - x_i$, G used to determine the intensity of group effectiveness, and $\hat{l}_{ij} = \frac{x_j - x_i}{l_{ij}}$ is an element trajectory from ith and jth grasshopper.

As mentioned above, the principal part of group interaction is the use of G. This use describes the motion orientation of each grasshopper in the swarm and determined according to Eq. (12):

$$S(r) = ke^{\frac{-r}{d}} - e^{-r} \tag{12}$$

where the strength of attraction is (k), and the attractive distance system is (d).

The above function produces two kinds of powers between each grasshopper: aversion and attraction. When the distance between every two grasshoppers is in [0, 2.079], they repulse each other to prevent a clash. The power of attraction grows if the distance is between [2.079, 4] to keep the swarm's coherence. If the distance is precisely 2.079, there is no power, and this state is named the rest area.

The simulation in interactions within grasshoppers produces a useful swarm model. Moreover, it should be modified to create an optimization approach. Related to refs. Saremi et al. (2017), and Aljarah et al. (2018) suggested the subsequent arithmetical design exploration while grasshoppers were interacting. The arithmetical design has been described according to Eq. (13):

$$X_i^l = c\left(\sum_{j=1, j\neq i}^{N} c\frac{ub_l - lb_l}{s} s\left(\left|x_j^l - x_i^l\right|\right)\frac{x_j - x_i}{l_{ij}}\right) + \hat{\mathrm{T}}_d \tag{13}$$

where the upper limit is (ub_l) in the lth length, the lower limit is (ub_l) in the lth length, ($\hat{T}_l$) is the amount of lth length the objective (best solution discovered yet), and (c) is a reducing coefficient to decrease the size of all three areas: rest, aversion, and attraction. Clearly, from this equation, the swarm improves the location near an objective ($\hat{T}_l$). The feature (c) makes the convergence of swarm gets an orientation to the objective. In the GOA algorithm, it has estimated that the aim has been achieved the best solution yet. While grasshoppers were interacting and keeping track of the objective, the optimal solution was improved when a more desirable solution was found.

The feature (c) is the essential regulation feature in the GOA algorithm and has been improved according to Eq. (14) (Aljarah et al., 2018):

$$c = c_{max} - i\left(\frac{c_{max} - c_{min}}{I}\right) \tag{14}$$

where the maximum iterations number is (I), the existing iteration is (i), c_{max} is equal to 1, and c_{min} is equal to 0.00001. The aforementioned illustrates the objective's location in a three-dimensional space more than 1000 iterations of the algorithm.

The mechanical implementation of the swarm motion near an objective in a three-dimensional space by the athletic model. Owing to the engagement of vectors in its model, it can be an increased number of dimensions. It is established that the GOA has been extremely useful in determining optimal solutions for difficult problems.

Despite the easiness, the suggested algorithm correctly approaches solutions near the most suitable exploration extent. The initial population was so significant in GOA due to the limitation of stochastic element numbers include the suggested algorithm. The GOA algorithm (excepting OGStHS in the suggested approach) was of the number of solutions, iterations, and variables. For this aspect, the distance of one grasshopper to the others must be determined in every dimension throughout iterations. Moreover, arithmetic complication takes into account the cost of the objective function, as illustrated in Eqs. (1) and (2) due to the variation of this problem.

4. Execution of GOA for optimal short-term hydrothermal scheduling

The implementation of the algorithm GOA method to solve the OGStHS problem is explained in detail in this section. The significant employment of the suggested approach is essentially based on the mechanism that handles the constraints. Therefore, this section essentially concentrates on this subject. Based on the properties of the OGStHS problem, it has been selected a collection of water release rates (Q_{hj}^{t}) as the results variables for hydro plants while applying a collection of energy productions (P_{si}^{t}) as the results variables for thermal plants. For a specific period of time (T) through the schedule extent, T will schedule water releases rates by Nh hydro plants and T to the energy production schedule by N_s thermal plants. Therefore, the solution description executed in this article to solve the OGStHS problem is as follows:

The scale of the components P_{si}^{t} and Q_{hj}^{t} must be satisfied with the capacity of thermal producing and the rate of water release constraints according to Eqs. (5) and (7). Considering the spillage in Eq. (9) is zero to make easiness, the hydraulic sequence constraints have to, as shown in Eqs. (15) and (16).

$$X = \begin{bmatrix} Q_{1,0} & Q_{2,0} & \cdots & Q_{N,0} & P_{s1,0} & P_{s1,0} & \cdots & P_{sN,0} \\ Q_{1,1} & Q_{2,1} & \cdots & Q_{N,1} & P_{s1,1} & P_{s2,1} & \cdots & P_{sN,1} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ Q_{1,T} & Q_{2,T} & \cdots & Q_{N,T} & P_{s1,T} & P_{s2,T} & \cdots & P_{sN,T} \end{bmatrix} \tag{15}$$

$$V_{hj}^{0} - V_{hj}^{T} = \sum_{t=1}^{T} Q_{hj}^{T} - \sum_{t=1}^{T} \sum_{l=1}^{Up} Q_{hl}^{T-tq} - \sum_{t=1}^{T} I_{hj}^{t}, \quad j \in N_h \tag{16}$$

Rate of water steam of jth reservoir at a specific period of time t is (I_{hj}^{t}), delay of a water passage from reservoir l to j is (t_q), and upstream units numbers straight overhead jth hydro plant is (U_p). To match precisely the constraints on the initial and final reservoir storage in Eq. (9), the rate of water release of the jth hydro plant Q_{hj}^{t} at a specific period of time t is determined by Eq. (17):

$$Q_{hj}^{t} = V_{hj}^{0} - V_{hj}^{t} + \sum_{t=1}^{T} I_{hj}^{t} + \sum_{t=1}^{T} \sum_{l=1}^{Up} Q_{hl}^{T-tq} - \sum_{\substack{t=1 \\ t\neq d}}^{T} Q_{hj}^{t}, \quad j \in N_h \tag{17}$$

The specific rate of water release should be satisfied with the constraints in Eq. (7). Moreover, to match precisely the constraints of power balance in Eq. (4), the thermal production (P_{si}^{t}) of the specific unit of thermal production (i) can be determined by using Eq. (18):

$$P_{si}^{t} = P_{D}^{t} - \sum_{\substack{i=1 \\ i\neq d}}^{Ns} P_{si}^{t} + \sum_{j=1}^{Nh} P_{hj}^{t}, \quad t \in T \tag{18}$$

The specific thermal production should be satisfied with the restrictions in Eq. (5). The function of cost F should be minimized as shown in objective function Eq. (1).

For more clarification on the optimization process, the suggested GOA flow chart has been illustrated in Fig. 1. Besides, stepwise procedure, i.e., a complete algorithm may then be expressed in steps as shown below:

- Step-1. Indiscriminately initialize the grasshopper's swarm population based on each unit's limitations, such as different lengths and exploring points. These initial grasshoppers swarm should be possible to elect the final decision that should be satisfied with grasshoppers to swarm operation constraints.
- Step-2. Made a comparison for every value of agent cost with that of its parameters includes G_i, G_r, and W_e. The agent with the best cost value has been signified as the best interaction based on Eq. (11).
- Step-3. Adjust the motion of each agent based on Eq. (12).
- Step-4. Adjust the interaction of each agent based on Eq. (13).
- Step-5. For each individual X-matrix in the population illustrated in Eq. (15), it must be determined the function of cost F consistent with Eq. (1).
- Step-6. If the newcomer value of cost for any ith agent is less than its earlier rate, the agent's newcomer arrangements would be kept as its G_i. For finding the best X_i^l value, the cost values of G_i are compared for every agent.
- Step-7. If iterations number gets to the maximum, then turn to the next step, else, return to adjust the interaction again.
- Step-8. For every individual that produces the most advanced, which is regarded as X_i^l is made a problem solution.

5. Results and discussion

The suggested algorithm is examined with two individual systems, the first system containing 9-buses, eleven-transmission-lines, 8 thermal plants, 6 hydro plants, and the second with an adjusted standard efficient system, including 65-buses 92-transmission-lines, twelve thermal plants, and eleven hydro plants. The suggested GOA is employed to make the solution to the OGStHS problem. To prevent fake results because of the stochastic characteristics of the GOA, 1000 trial runs have been executed with various random populations at every run. The extent of the population was 60-agents in the whole run. The simulation has been performed on a core i7, 8th Gen with a 2.00 GHz processor.

From the aspect of convergence of the hydrothermal scheduling of a fitness function for better five individuals (ind) than others of II system using suggested GOA algorithm has been displayed in Fig. 2. The convergence feature of the fitness function has been described by selecting the original value of minimum fitness when iterations reached to end. It can be observed from Fig. 2 that convergence of fitness function gets to the optimum value easily with no sudden oscillations. This displays the accuracy of convergence for the suggested algorithm.

Fig. 3 displays the daily load curve of the I system and the adjusted II system. Fig. 4 demonstrates the paths of the optimal release of the hydro plants of the I system. It may be noticed from

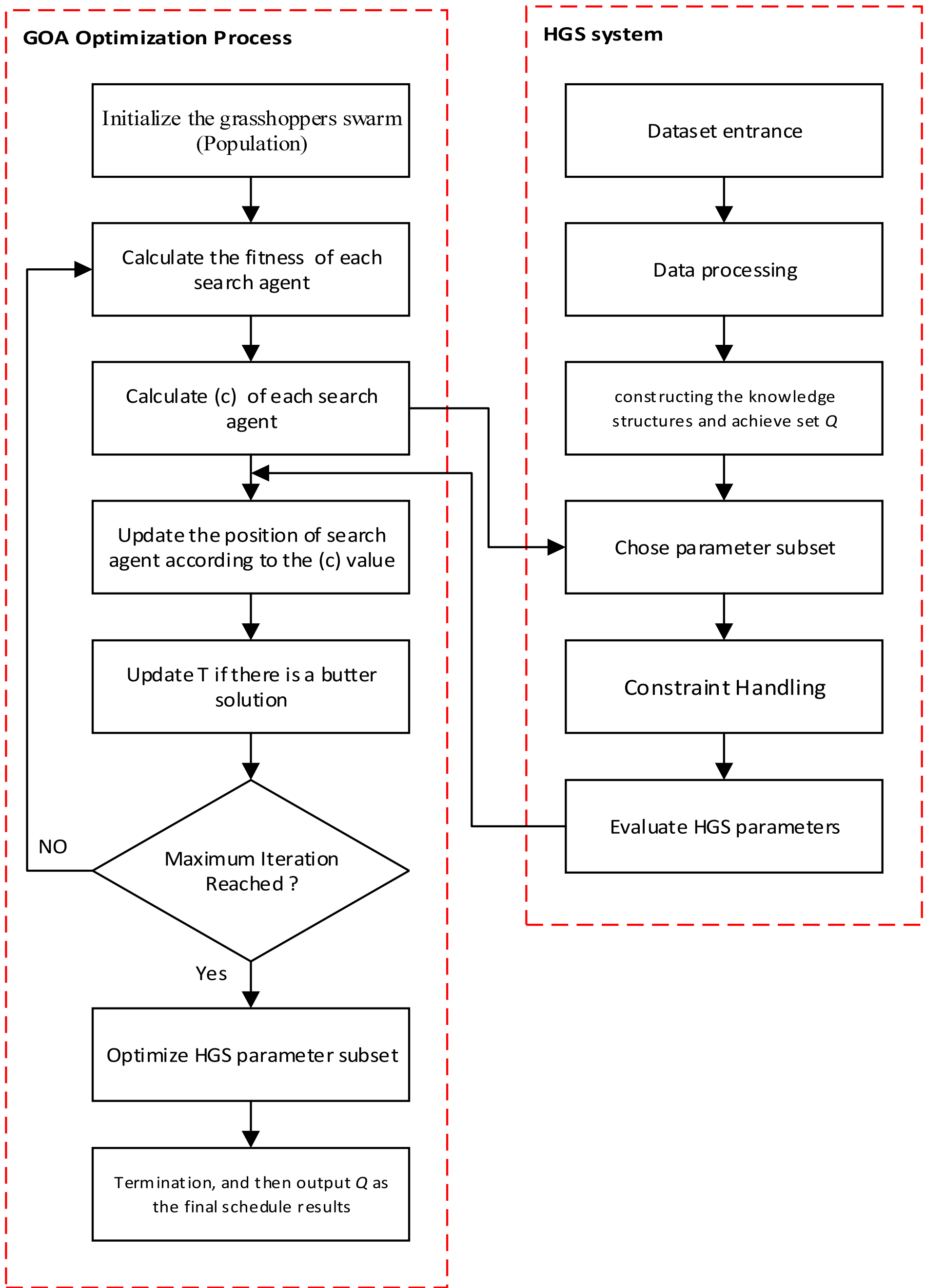

Fig. 1. Schematic diagram of the proposed GOA-HGS model.

Fig. 4 that the paths of hydro release achieved by the suggested GOA exceedingly correspond with the daily load curve.

According to the I system, Fig. 5 displays the Pareto distribution for best final decisions in Q received by GOA and improved generic algorithm type 2 (GA-2) (Lu et al., 2011). It regards as an objective function value of gotten absolute decision methods. In comparison, all aspects of the generations for hydrothermal power and water release rates of GOA's optimal adjustment schedule solutions are delivered in Table 1. The reservoir storage volumes per hour of the optimal adjustment schedule solutions have also been evaluated to verify whether the problem constraints have been satisfied or not to be.

From Fig. 5, we may also see the performance for handling the suggested GOA system is extremely better than the solutions achieved through GA-2. According to Fig. 5, the Pareto optimal appearance presented separately through the best non-dominated results in Q achieved through GOA has been nearer to the real Pareto appearance than that of GA-2. While from Fig. 5, we may notice that the Pareto best results achieved by GOA are adequately distributed on the best appearance. Though the Pareto best results achieved by GA-2 are appropriately distributed, the variegation characteristics are not as well as the ones archived by GOA.

For the II system, it can be noticed, according to Fig. 6, that GOA can make a solution to this system with satisfying performance while GA-2 cannot be. As displayed in Fig. 6, the Pareto best results achieved by GOA are properly dispersed on the appearance with satisfying variety. Their convergence characteristics are better than the solutions achieved through GA-2. Furthermore, from Fig. 6, it can be assumed that GA-2 cannot deal with this type of system because the Pareto best results achieved

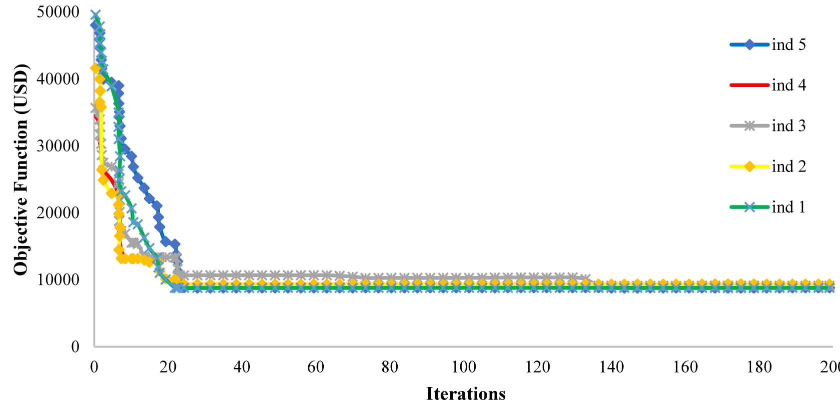

Fig. 2. Convergence characteristics of II system.

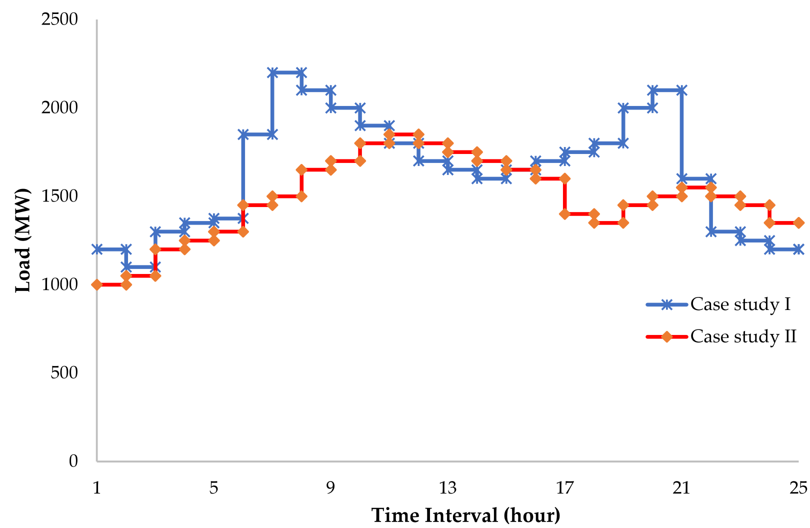

Fig. 3. Load curve for I system and II system.

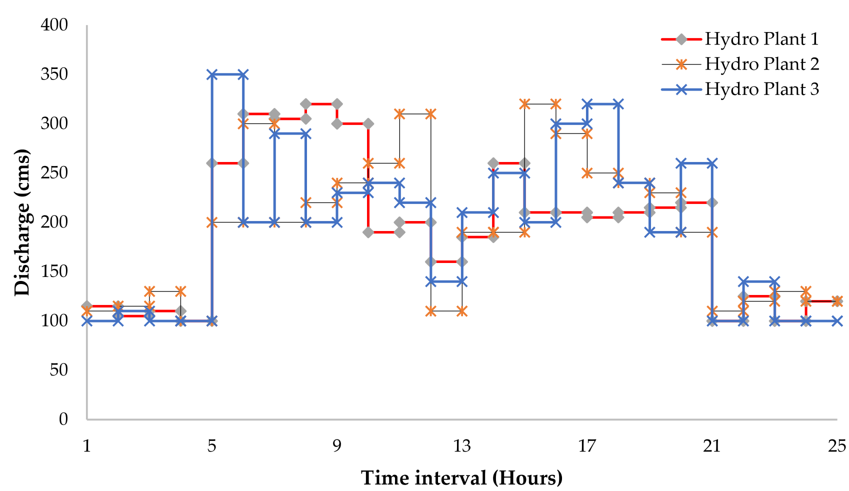

Fig. 4. Release paths of hydro plants – I system.

by it have been dispersed irregular on various Pareto appearances. Therefore, the suggested GOA approach's convergence and variegation characteristics for solving this type of system are adequately proved.

Simultaneously, with data arranged in Table 1 and displayed in Fig. 7, the rigid restriction requirements of the optimal adjustment schedule results achieved through GOA have been verified to confirm the suggested approach's effectiveness. Based on Table 1 and Fig. 7, it is understood that the consideration of the transmission loss has grown the challenges of the problem significantly. The restrictions processing plans originated in this study can handle the complex restrictions of the OGStHS problem efficiently. The final decisions of scheduling achieved by the suggested GOA approach can be satisfied entire types of

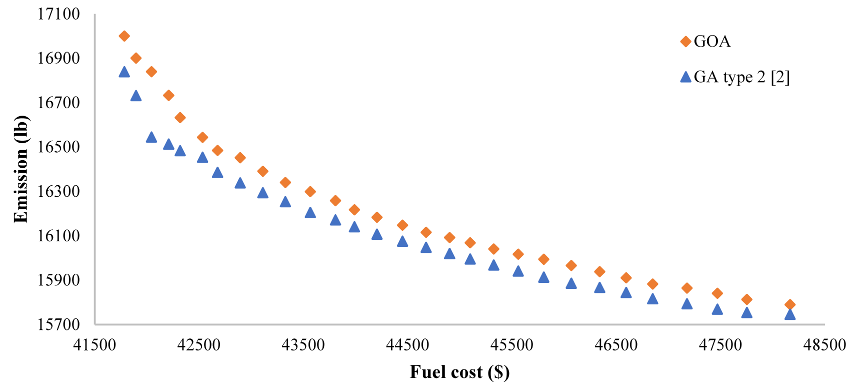

Fig. 5. Pareto optimal front obtained by a different method for the I system.

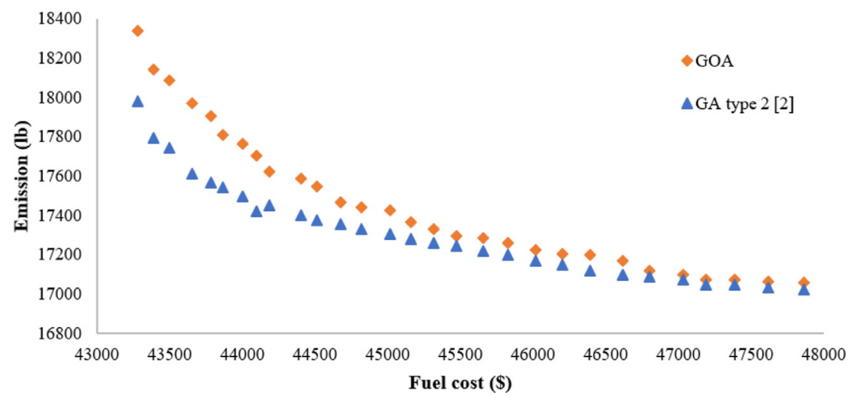

Fig. 6. Various methods achieve Pareto best appearance.

Table 1
The aspects of the optimal compromise solution achieved by GOA.

Hour	Water discharge rates $\times$ 10^4 m^3				Hydro generations in MW				Thermal generations in MW			Total in MW
1	8.624	7.111	27.552	7.111	81.686	58.721	15.597	141.601	181.587	189.111	147.95	816.253
2	8.68	7.111	26.611	7.111	82.743	59.885	15.652	138.748	183.933	216.77	148.522	846.253
3	8.299	7.111	24.54	7.111	80.481	61.017	22.991	135.465	182.8	134.045	149.454	766.253
4	8.403	7.111	21.605	7.111	81.41	62.655	34.924	131.346	127.766	133.912	144.239	716.252
5	7.009	7.111	18.935	7.111	70.755	64.221	44.309	125.543	151.949	134.117	145.358	736.252
6	6.692	7.111	18.937	7.111	68.137	65.225	43.604	144.428	184.123	211.839	148.897	866.253
7	11.422	9.092	18.169	12.14	99.163	78.989	45.948	223.348	184.123	232.102	152.58	1016.253
8	11.378	9.194	17.699	16.887	98.204	78.569	46.448	280.713	184.123	224.769	163.428	1076.254
9	11.144	9.189	19.017	18.793	96.709	77.955	40.815	300.196	184.123	218.939	237.516	1156.253
10	10.398	8.947	19.697	18.937	92.997	76.443	37.884	301.385	184.096	218.997	234.45	1146.252
11	11.18	9.704	18.788	18.169	97.436	81.562	41.676	295.62	184.123	227.706	238.13	1166.253
12	10.788	9.397	19.392	17.699	96.139	79.999	40.063	291.914	184.123	301.208	222.807	1216.253
13	10.701	9.625	19.642	19.017	95.793	81.174	39.557	301.963	184.123	236.887	236.757	1176.254
14	10.592	10.241	19.892	19.697	95.631	84.322	40.034	306.733	184.123	233.177	152.232	1096.252
15	10.384	10.18	19.067	18.788	95.176	83.921	44.308	300.295	184.123	219.63	148.8	1076.253
16	10.293	10.506	18.178	19.392	95.091	85.619	48.464	304.628	184.123	238.034	170.293	1126.252
17	10.393	10.996	17.299	19.642	95.846	87.307	52.025	306.354	184.123	224.975	165.625	1116.255
18	10.244	11.544	16.855	19.892	94.936	88.187	54.602	308.044	184.123	221.456	234.905	1186.253
19	10.286	12.181	16.467	21.103	94.91	88.139	56.948	315.674	184.123	223.546	172.913	1136.253
20	10.262	12.997	16.176	21.101	94.233	88.5	58.877	313.575	184.123	220.42	156.525	1116.253
21	6.15	10.715	12.752	20.137	63.689	76.239	62.197	304.658	184.123	136.109	149.238	976.253
22	6.121	11.44	13.137	20.138	63.72	79.165	64.805	301.736	136.438	134.036	146.354	926.254
23	6.111	11.863	13.899	20.795	64.023	80.012	67.243	302.242	121.173	134.031	147.529	916.253
24	6.111	8.185	13.506	20.766	64.426	58.903	68.156	297.355	113.899	134.31	129.204	866.253

this system constraints. Therefore, the GOA approach's successful employment to solve the OGStHS problem is adequately proved again. Simultaneously, the productions of hydrothermal power and rates of water release of the optimal adjustment schedule solution achieved by GOA have been arranged in Table 1, and its reservoir storage volumes per hour have been displayed in Fig. 7 to verify the contentment conditions to constraints.

Moreover, the optimal power production and rate of reservoir release for only I system have been displayed in Fig. 8, which regards statistical analysis. It was evident from Fig. 8 that the suggested method provides practical and best results. To verify the efficiency of the suggested GOA, it has been made a comparison with the Decomposition Approach (DA) and the LP method and the GA as described in the previously completed works section of

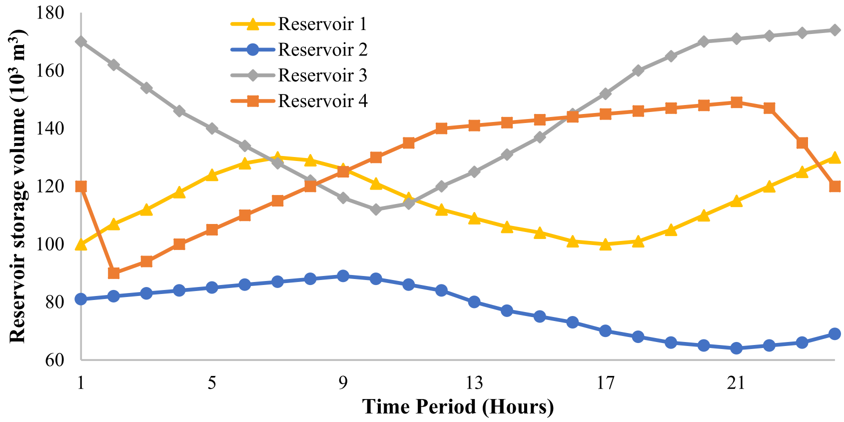

Fig. 7. Scheme of hourly hydro reservoir volumes of the optimal adjustment scheduling achieved by GOA.

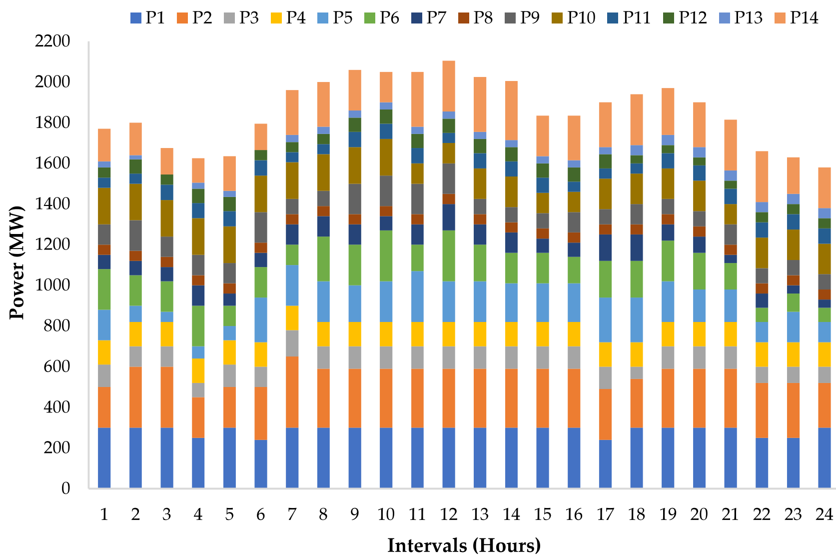

Fig. 8. Optimal power generation achieved by GOA technique.

Table 2
Comparison of cost and time of a 66-bus utility system (For I system).

Method	Time (s)	Cost ($)			Processor
		Min	Mean	Max	
DP (Lakshminarasimman and Subramanian, 2006)	–	928,919.15	–	–	C++ code on a Pentium-IV
DE (Wang et al., 2012b)	8.69	923,991.08	925,157.28	928,395.84	Delphi 2010 on a P-IV
IPSO (Hota et al., 2009)	38.46	922,553.49	–	–	Matlab-7.0 on a P-IV
DRQEA (Wang et al., 2012b)	7.98	922,526.73	923,419.37	925,871.51	Delphi 2010 on a P-IV
CRQEA (Wang et al., 2012a)	–	922,477.14	–	–	Delphi 2010 on a P-IV
MAPSO (Amjady and Soleymanpour, 2010)	64	922421.66	922,544	923,508	–
TLBO (Roy, 2013)	–	922,373.39	922,462.24	922,873.81	Core 2 duo
RCGA-AFSA (Carvalho and Soares, 1987)	11	922,339.625	922,346.323	922,362.532	Microcomputer (64 kB)
SPPSO (Zhang et al., 2011)	16.3	922,336.31	923,083.48	922,362.532	C++code in the Linux (Core 2 Duo)
DNLPSO (Rasoulzadeh-Akhijahani and Mohammadi-Ivatloo, 2015)	37	922,498	922,837	923,580	–
MDNLPSO (Rasoulzadeh-Akhijahani and Mohammadi-Ivatloo, 2015)	35	922,336.3	922,676.2	923,404.5	–
SOS (Das and Bhattacharya, 2018)	6.21	922,332.1691	922,338.1982	922,482.8956	MATLAB-2013 on a core i3
GA (Kumar and Mohan, 2011)	4.9	–	–	78,757.12	Pentium(R)
DA and LP method (Mohan et al., 1992)	56.2	–	–	78,654.86	WIPRO-386
Proposed GOA	3.8	78,650	78,653.56	78,657.12	Core i7-8th

introduction (Mohan et al., 1992) and Kumar and Mohan (2011) respectively.

The I system and II system data from the mentioned section are taken into account for making this performance differentiation. Table 2 displays the differentiation of cost and achievement period for the I system. Furthermore, this section has been used to compare the present study results with other major studies to solve the SHS problem using various modern techniques. In this comparison, the focused methods include the DP, DE, improved PSO (IPSO), differential real-coded quantum-inspired evolutionary algorithm (DRQEA), modified adaptive PSO (MAPSO), hybrid of real coded genetic algorithm and artificial fish swarm algorithm (RCGA-AFSA), small population PSO (SPPSO), dynamic neighborhood learning PSO (DNLPSO), modified DNLPSO

Table 3
Comparison of cost and time of a 66-bus utility system (For II system).

Method	Time (s)	Cost ($)		
		Min	Mean	Max
TLBO (Roy, 2013)	–	–	–	423,858.78
PSO (Das and Bhattacharya, 2018)	125.32	318,970	319,350.84	320,874.21
SOS (Das and Bhattacharya, 2018)	46.25	314,994.38	315,052.3	315,718.42
GA (Kumar and Mohan, 2011)	12.765	–	–	226,205.76
DA and LP method (Mohan et al., 1992)	89.4	–	–	220,537.46
Proposed GOA	11.654	219,899.24	220,025.5	220,205.76

Table 4
p values of Wilcoxon signed-rank test result for GOA algorithm.

	GOA versus GA-2	GOA versus GA
I System	8.2021E−10	10.5354E−10
II System	9.9757E−10	11.7576E−10

(MDNLPSO), symbiotic organisms search (SOS), DA, LP, and GA technique.

It has been found out that the cost of the suggested GOA is relatively similar to that of the DA, LP, and GA technique, and the achievement time of the suggested GOA is significantly less when we made a comparison with that of the DA, LP, and GA technique. Thus, GOA's maximum and the average cost is better than that of other methods described in the above section. In the same regard, Table 3 displays the differentiation of cost and achievement period for the II system used. For comparing system 11, TLBO, PSO, SOS, GA, DA, and LP methods were used.

Nevertheless, Table 3 (II system) has got the same range results as Table 2 (I System). The GOA is better after the comparison of the cost values. These were relatively similar to that of the DA, LP, and GA technique, and the achievement time of the suggested GOA is significantly less. Thus, GOA's maximum and the average cost is better than that of other methods described in Tables 2 and 3.

To validate the analysis' performance statistically, forty confident trials have been provided to GA, improved GA-2, and GOA. In contrast, the whole selection features of algorithms have been established to be corresponding to the OGStHS analysis system. The cost and time of achieved solutions by DA, LP, GA, and GOA techniques have been displayed in Table 4, and it was evident from these solutions that GOA outperforms other methods.

Therefore, it is shown that the GOA method has a very less sensitive effect on the initial results. In this study, to compare the performance of GOA with GA and GA-2, nonparametric Wilcoxon signed-rank analysis has been employed in the analysis system. The Wilcoxon signed-rank analysis support to distinguish the critical variation between two individual means (Derrac et al., 2011). The investigation has been completed at a level of importance $\alpha = 0.01$. Results analysis is listed in Table 4, and it has been recognized that there is an important variance between GOA in comparison with GA and GA-2 method.

6. Conclusion

The OGStHS has been a complex arithmetic optimization problem with extremely nonlinear and calculational exorbitant conditions. The study presented a method to solve this problem by the GOA method in which whole variables have been considered without obtaining the common facilitate presumptions needed by traditional methods. The suggested algorithm GOA has been examined on two individual systems. The GOA system displays the high ability to explore the optimal generation schedule due to the main factor: group interaction of employment swarms. Moreover, each other factors (gravity and wind effect horizontally) improve the searching ability of the used algorithm. As a result, GOA decreases the difficulty and computation time and provides a globally optimum solution. We have made a comparison to the DA, LP, and GA method. Moreover, the suggested method's robustness has been made a validation using executing the non-parametric Wilcoxon signed-rank analysis. Overall, it is realized that the GOA approach may reach more reliable solutions for the OGStHS with robust performance in less computational time than the recent techniques.

CRediT authorship contribution statement

Xie Zeng: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Funding acquisition. **Ali Thaeer Hammid:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft. **Nallapaneni Manoj Kumar:** Conceptualization, Formal analysis, Supervision, Visualization, Writing - review & editing. **Umashankar Subramaniam:** Writing - review & editing, Funding acquisition. **Dhafer J. Almakhles:** Writing - review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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