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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 (OGSHTS) with the deliberation of various purposes is a complex non-linear constrained optimization problem. There exist numerous constraints, which make the OGSHTS 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 OGSHTS 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 OGSHTS problem. Meantime, a grasshopper optimization algorithm (GOA) is performed to handle the OGSHTS problem by getting optimized for both objectives concurrently. A modern approach is shown in this study to get a solution to the OGSHTS 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.

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1. Introduction

The short-term hydrothermal scheduling (SHS) is the most concerning problem for ensuring an interrelated power system’s optimal operation. In the hydrothermal power system (HPS), the SHS problem refers to the optimal generation for short-term hydrothermal scheduling (OGSHTS). 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 OGSHTS 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 OGSHTS problem may be classified as an extensive, robust, nonlinear, and non-convex optimization problem with different complex constraints, determining the final
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 (Lakshminarasimhan 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 (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. Sarem 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 ($N_t$) with interval times ($T$) is expressed by Eq. (1) (Das and Bhattacharya, 2018):

$$F = \min \sum_{i=1}^{N_t} \sum_{j=1}^{Nh} f_i (P_{i,j}^t)$$  \hspace{1cm} (1)

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

$$f_i (P_{i,j}^t) = x_i + (y_i \cdot P_{i,j}^t) + (z_i \cdot P_{i,j}^t)^2 + a_i \sin (b_i \cdot (P_{i,j}^t - P_{i,min}^t))$$ \hspace{1cm} (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 for 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 $i$. $P_{i,min}^t$ 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 $j$th hydro plant at a specific period of time ($t$), power generation is determined by Eq. (3):

$$P_{j,j}^t = z_{j} (V_{j,j}^t)^2 + z_{j,j} (Q_{j,j}^t)^2 + z_{j,j} (V_{j,j}^t Q_{j,j}^t)^2 + z_{j} V_{j,j}^t + z_{j,j} Q_{j,j}^t + z_{j}$$ \hspace{1cm} (3)

where the power production of the $j$th hydro plant is ($P_{j,j}^t$) at a specific period of time ($t$). $z_{j,j}$, $z_{j,j}$, $z_{j,j}$, $z_{j,j}$, $z_{j}$, and $z_{j}$ are the coefficients. $V_{j,j}^t$ is the volume of the $j$th hydro plant at a specific period of time ($t$). $Q_{j,j}^t$ is the water release of the $j$th 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):

$$\sum_{i=1}^{N_t} P_{i,j}^t + \sum_{j=1}^{Nh} P_{j,j}^t = P_{i,j}^t + P_{lossj}$$ \hspace{1cm} (4)

where the gross demand for the load is ($P_{i,j}^t$) at a specific period of time ($t$). The number of thermal and hydro plants is ($N_t$) and ($Nh$), 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):

\[
P_{t_i, \text{min}} \leq P_{t_i} \leq P_{t_i, \text{max}}
\]

\[i = 1, 2, \ldots, N_t, t = 1, 2, \ldots, T\]  \hspace{1cm} (5)

where the minimum and the maximum energy production of the \(i\)th thermal plant are \(P_{t_i, \text{min}}\) and \(P_{t_i, \text{max}}\) 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):

\[
P_{t_j, \text{min}} \leq P_{t_j} \leq P_{t_j, \text{max}}
\]

\[j = 1, 2, \ldots, N_h, t = 1, 2, \ldots, T\]  \hspace{1cm} (6)

where the minimum and the maximum energy production of the \(j\)th hydro plant are \(P_{t_j, \text{min}}\) and \(P_{t_j, \text{max}}\) 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):

\[
Q_{t_j, \text{min}} \leq Q_{t_j} \leq Q_{t_j, \text{max}}
\]

\[j = 1, 2, \ldots, N_h, t = 1, 2, \ldots, T\]  \hspace{1cm} (7)

where the minimum and the maximum water release of the \(j\)th hydro plant are \(Q_{t_j, \text{min}}\) and \(Q_{t_j, \text{max}}\) 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):

\[
V_{t_j, \text{min}} \leq V_{t_j} \leq V_{t_j, \text{max}}
\]

\[j = 1, 2, \ldots, N_h, t = 1, 2, \ldots, T\]  \hspace{1cm} (8)

where the minimum and the maximum volumes of the \(j\)th hydro plant are \(V_{t_j, \text{min}}\) and \(V_{t_j, \text{max}}\) respectively.

2.2.7. Balance of water dynamic

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

\[
V_{t_j} = V_{t_j}^{t-1} + I_{t_j} - Q_{t_j} + \sum_{m=1}^{N_j} Q_{t_m}^{t-\lambda_mj}
\]

\[j = 1, 2, \ldots, N_h, t = 1, 2, \ldots, T\]  \hspace{1cm} (9)

where the entire of upstream hydro plants straight overhead the \(j\)th 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):

\[
V_{t_j}^0 = V_{t_j, \text{ini}}; V_{t_j}^T = V_{t_j, \text{fin}}
\]

\[j = 1, 2, \ldots, N_h\]  \hspace{1cm} (10)

where the initial and final reservoir storage of the \(j\)th hydro plant is \(V_{t_j, \text{ini}}\) and \(V_{t_j, \text{fin}}\) respectively.

3. Grasshopper optimization algorithm for hydrothermal scheduling

The GOA algorithm has been suggested to address the problem of OGSHS, 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 \((G_m)\), and wind effect horizontally \((W_c)\). In the GOA algorithm, group interaction is the principal procedure of exploration determined according to Eq. (11):

\[
G_i = \sum_{j=1, j \neq i}^{N} G_i(l_{ij}) \hat{l}_{ij}
\]

\[i = 1, 2, \ldots, N, j = 1, 2, \ldots, N\]  \hspace{1cm} (11)

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

\[
S(r) = ke^{-d^2} - e^{-d^2}
\]

\[0 < d < \infty\]  \hspace{1cm} (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):

\[
X_{i}^{t} = c \left( \sum_{j=1, j \neq i}^{N} c \frac{u_{bi} - lb_{bi}}{s} \left( |x_{j} - x_{i}| \right) \frac{x_{j} - x_{i}}{l_{ij}} \right) + \hat{T}_{d}
\]

\[t = 1, 2, \ldots, T\]  \hspace{1cm} (13)

where the upper limit is \((ub_{bi})\) in the \(i\)th length, the lower limit is \((lb_{bi})\) in the \(i\)th length, \((T_{d})\) is the amount of \(i\)th 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 \((T_{d})\). 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):

\[
c = c_{\text{max}} - i \left( \frac{c_{\text{max}} - c_{\text{min}}}{l} \right)
\]

\[l = \text{maximum iterations number is (l)}, \ c_{\text{max}} \text{ is equal to 1}, \ c_{\text{min}} \text{ is equal to 0.00001}\]  \hspace{1cm} (14)

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 \(Q^t_{Dj}\) as the results variables for hydro plants while applying a collection of energy productions \(P_{sl}^t\) 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 \(N_t\) thermal plants. Therefore, the solution description executed in this article to solve the OGStHS problem is as follows:

The scale of the components \(P_{sl}^t\) and \(Q^t_{Dj}\) 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).

\[
X = \begin{bmatrix}
Q_{1,0} & Q_{2,0} & \cdots & Q_{N_t,0} & P_{s1,0} & P_{s1,1} & \cdots & P_{sN_t,0} \\
Q_{1,1} & Q_{2,1} & \cdots & Q_{N_t,1} & P_{s1,1} & P_{s1,2} & \cdots & P_{sN_t,1} \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\
Q_{1,T} & Q_{2,T} & \cdots & Q_{N_t,T} & P_{s1,T} & P_{s2,T} & \cdots & P_{sN_t,T}
\end{bmatrix}
\]

(15)

\[
V_{0j}^t - V_{Dj}^t = \sum_{t=1}^{T} Q_{bj}^t - \sum_{t=1}^{T} \sum_{l=1}^{U_p} Q_{bj}^t - T \sum_{t=1}^{T} l_{bj}^t,
\]

\[
\sum_{t=1}^{T} l_{bj}^t = Q_{bj}^t.
\]

(16)

\[
Q_{bj}^t = V_{0j}^t - V_{Dj}^t + \sum_{t=1}^{T} l_{bj}^t + \sum_{t=1}^{T} \sum_{l=1}^{U_p} Q_{sl}^t - T \sum_{t=1}^{T} l_{bj}^t,
\]

\[
\sum_{t=1}^{T} l_{bj}^t = Q_{bj}^t.
\]

(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 \(P_{sl}^t\) of the specific unit of thermal production \(i\) can be determined by using Eq. (18):

\[
p_{sl}^t = P_{sl}^t - \sum_{i=1}^{Ns} p_{sl}^t + \sum_{j=1}^{Nh} p_{sl}^t,
\]

\[
t \in T.
\]

(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 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 \(G_i\), \(G_e\), and \(W\). 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 \(X^t_i\) 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 \(X^t_i\) 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. 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
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. 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.
Fig. 5. Pareto optimal front obtained by a different method for the I system.

Fig. 6. Various methods achieve Paretobest appearance.

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

<table>
<thead>
<tr>
<th>Hour</th>
<th>Water discharge rates $\times 10^6$ m$^3$</th>
<th>Hydro generations in MW</th>
<th>Thermal generations in MW</th>
<th>Total in MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8.624</td>
<td>7.111</td>
<td>27.552</td>
<td>141.601</td>
</tr>
<tr>
<td>2</td>
<td>8.88</td>
<td>7.111</td>
<td>26.611</td>
<td>141.601</td>
</tr>
<tr>
<td>3</td>
<td>8.299</td>
<td>7.111</td>
<td>24.54</td>
<td>139.197</td>
</tr>
<tr>
<td>4</td>
<td>8.403</td>
<td>7.111</td>
<td>23.605</td>
<td>134.24</td>
</tr>
<tr>
<td>5</td>
<td>7.009</td>
<td>7.111</td>
<td>18.935</td>
<td>126.152</td>
</tr>
<tr>
<td>6</td>
<td>6.692</td>
<td>7.111</td>
<td>18.937</td>
<td>128.887</td>
</tr>
<tr>
<td>7</td>
<td>11.422</td>
<td>9.092</td>
<td>18.169</td>
<td>126.152</td>
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<td>10.506</td>
<td>19.187</td>
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<td>11.544</td>
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<td>12.181</td>
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<td>12.997</td>
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<td>24</td>
<td>6.111</td>
<td>8.185</td>
<td>13.506</td>
<td>112.034</td>
</tr>
</tbody>
</table>

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

Moreover, the optimal power production and rate of reservoir release for only 1 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 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.
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

<table>
<thead>
<tr>
<th>Method</th>
<th>Time (s)</th>
<th>Cost ($)</th>
<th>Processor</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP (Lakshminarasimman and Subramanian, 2006)</td>
<td>–</td>
<td>928,919.15</td>
<td>C++ code on a Pentium-IV</td>
</tr>
<tr>
<td>DE (Wang et al., 2012b)</td>
<td>8.69</td>
<td>923,991.08</td>
<td>Delphi 2010 on a P-IV</td>
</tr>
<tr>
<td>IPSO (Hota et al., 2009)</td>
<td>38.46</td>
<td>922,553.49</td>
<td>Matlab-7.0 on a P-IV</td>
</tr>
<tr>
<td>DRQEA (Wang et al., 2012b)</td>
<td>7.98</td>
<td>922,526.73</td>
<td>Delphi 2010 on a P-IV</td>
</tr>
<tr>
<td>CRQEA (Wang et al., 2012a)</td>
<td>–</td>
<td>922,477.14</td>
<td>Delphi 2010 on a P-IV</td>
</tr>
<tr>
<td>MAPSO (Amjadi and Soleymanpour, 2010)</td>
<td>64</td>
<td>922,421.66</td>
<td>923,508</td>
</tr>
<tr>
<td>TLBO (Roy, 2013)</td>
<td>–</td>
<td>922,373.39</td>
<td>922,462.24</td>
</tr>
<tr>
<td>RCGA-AFSA (Carvalho and Soares, 1987)</td>
<td>11</td>
<td>922,339.625</td>
<td>922,346.323</td>
</tr>
<tr>
<td>SPPSO (Zhang et al., 2011)</td>
<td>16.3</td>
<td>922,336.31</td>
<td>922,362.532</td>
</tr>
<tr>
<td>MDNLPSO (Rasouli-Zadeh-Akhjahani and Mohammadi-Ivatloo, 2015)</td>
<td>35</td>
<td>922,336.3</td>
<td>922,676.2</td>
</tr>
<tr>
<td>SOS (Das and Bhattacharya, 2018)</td>
<td>6.21</td>
<td>922,332.1691</td>
<td>922,338.1982</td>
</tr>
<tr>
<td>GA (Kumar and Mohan, 2011)</td>
<td>4.9</td>
<td>–</td>
<td>78,757.12</td>
</tr>
<tr>
<td>DA and LP method (Mohan et al., 1992)</td>
<td>56.2</td>
<td>–</td>
<td>78,654.86</td>
</tr>
<tr>
<td>Proposed GOA</td>
<td>3.8</td>
<td>78,650</td>
<td>Core i7-8th</td>
</tr>
</tbody>
</table>

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, respectively.
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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