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A Novel Gradient Based Optimizer for Solving Unit Commitment Problem

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ABSTRACT Secure and economic operation of the power system is one of the prime concerns for the engineers of 21st century. Unit Commitment (UC) represents an enhancement problem for controlling the operating schedule of units in each hour interval with different loads at various technical and environmental constraints. UC is one of the complex optimization tasks performed by power plant engineers for regular planning and operation of power system. Researchers have used a number of metaheuristics (MH) for solving this complex and demanding problem. This work aims to test the Gradient Based Optimizer (GBO) performance for treating with the UC problem. The evaluation of GBO is applied on five cases study, first case is power system network with 4-unit and the second case is power system network with 10-unit, then 20 units, then 40 units, and 100-unit system. Simulation results establish the efficacy and robustness of GBO in solving UC problem as compared to other metaheuristics such as Differential Evolution, Enhanced Genetic Algorithm, Lagrangian Relaxation, Genetic Algorithm, Ionic Bond-direct Particle Swarm Optimization, Bacteria Foraging Algorithm and Grey Wolf Algorithm. The GBO method achieve the lowest average run time than the competitor methods. The best cost function for all systems used in this work is achieved by the GBO technique.

INDEX TERMS Unit commitment, power system, gradient based optimizer.

ABBREVIATIONS

ACO	– Ant Colony Optimization.
BWA	- Binary Whale Algorithm.
BASA	- Binary Artificial Sheep Algorithm.
BMFO-SIG	- Binary Moth Flame Optimizer Algorithm with Sigmoidal Transformation.
BFA	– Bacteria Foraging Algorithm.
BFMO	- Binary Fish Migration Algorithm.
BGSA	- Binary Grasshopper Optimization Algorithm.
CHP	- Combined Heat and Power.
CSA	- Cuckoo Search Algorithm.
DA	- Dragonfly Algorithm.
DE	- Differential Evolution.
EGA	- Enhanced GA.
IBPSO	– Ionic Bond-direct Particle Swarm Optimization.
GA	- Genetic Algorithm.
GBO	– Gradient Based Optimizer.
GSA	- Gravitational Search Algorithm.
GWO	- Grey Wolf Optimization.
HS	- Harmony Search.
LR	- Lagrangian Relaxation.
MILP	- Mixed Integer Linear Programming.
PHEV	- Plugged In Hybrid Vehicle.
PVS	- Passive Vehicle Search.
PSA	- Penguin Search Algorithm.
SCA	- Sine Cosine Algorithm.
UC	- Unit Commitment.

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I. INTRODUCTION

Modern power system is becoming diverse and complex and secure in addition to power system economic operation is one of the prime concerns for the engineers of 21st century [1]. Unit Commitment (UC) assists an electricity provider to determine which power generators to run at which times and at what level, so as to satisfy the demand for electricity. UC is an enhancement issue for determining the operating timetable of the units in each hour with different loads at various technical and environmental constraints. UC is one of the complex optimization tasks performed by power plant engineers for regular planning and operation of power system [1], [2].

Researchers have used a number of metaheuristics (MH) such as GA, PSO, ACO, GWO etc for solving this complex and demanding problem. In [1], authors have used Binary Grey Wolf Optimization (GWO) for solving the UC problem for 100-unit, 80-units, 40-units, 20-units, and 10-unit system. In [2], the authors have proposed a mix optimizer of GA and MILP for solving UC. In [3], the authors have formed the UC problem for CHP in a multi-objective framework with operating cost and net emission as objective functions. The same problem was solved by using multi-objective PSO. In [4], the UC problem is modelled considering hydropower and solar in a robust platform and solved the same by CSA. In [5], the authors have used BWA to solve profit-based UC in competitive power market. In [6], the authors have used novel SCA for solving unit commitment of thermal units.

In [7], the authors have used the UC problem for thermal units in attendance of PHEVs. The same problem was solved by PVS algorithm simulated by passing vehicles on highways of two-lane rural. In [8], the authors have modelled the unit commitment problem considering pumped storage and renewable sources. Further, the authors have proposed a novel BASA mimicking the social behavior of sheep for solving the issue. In [9], the authors have used a novel DA PSO algorithm considering hybridization of DA and PSO for solving unit commitment. Simulation results demonstrated that the DA PSO performed better than the stand-alone algorithms for solving the complex UC problem. In [10], authors performed the forceful generation scheduling of a thermal power plant by SCA. In [11], authors have proposed a novel BMFO-SIG for solving unit commitment of a conventional power plant with and without wind resources. In [12], authors have validated the performance of novel BFMO for solving UC issue for different IEEE test networks. In [13], authors have used PSA, a metaheuristic mimicking social behavior of penguins for solving the demanding and complex unit commitment problem.

In [14], the authors have proposed an improved version of PSO possessing an improved strategy to deal with the binary decision variables for solving unit commitment in a micro grid having battery energy storage. Further, in [14], the battery degradation cost was also taken into account. In [15], a binary CSA was performed for solving the UC of a standard 4-unit system. In [16], a novel BGSA was performed for solving constrained UC problem. In [17], authors have hybridized HS with a random search strategy in order to solve unit commitment problem for various IEEE test beds. In [18], authors have used a quantum inspired binary GSA for solving the UC problem for various IEEE test beds. In [19], authors have used novel BWA for solving stochastic profit-based UC in a smart city environment. In [20], authors have hybridized GA and DE for solving basic unit commitment problem. In [21], authors have modelled the unit commitment during natural calamities such as hurricanes and used machine learning assisted approach to solve it. In [22], authors have modelled the unit commitment problem for hydropower plants considering multiple hydraulic heads by a two-layer nested optimization approach with Cuckoo Search (CS) and dynamic programming. In [23], authors have modelled the unit commitment problem as Markov process and then applied tree search and reinforcement learning for its solution. The approach is validated on 30-unit test system. The reinforcement learning based approach outperformed mixed integer linear programming [23]. In [24], the authors proposed a novel Bayesian Optimization approach for unit commitment problem. In [25], the authors modelled a security constrained scenario-based unit commitment problem considering battery energy storage and solved the problem by deep learning. They concluded that incorporating battery energy storage could reduce the operating cost by 4.7%. In [26], authors modelled the unit commitment considering hydropower for Quebec, Canada and solved the same by applying Mixed Integer Linear programming. In [27], authors formulated the unit commitment problem considering random generation of wind power and solved the same by Mixed Integer Linear programming. In [28], the authors formulated price based stochastic unit commitment and solved the same by Bender's decomposition method. In [29], the authors proposed a novel polar bear optimization algorithm for solving scalable unit commitment problem. In [30], authors proposed a scalable security constrained unit commitment and solved the same by cone programming method. A brief description of existing research works on UC is presented in Table 1. The existing algorithms reported in [1]–[30] used for solving UC sometimes suffer from shortcomings such as getting stuck in local optima, poor balance between exploitation and exploration, time complexity etc.

The main motivation that inspires us to use GBO is the theorem of No Free Lunch (NFL) which states that any single algorithm cannot equally perform better in all the optimization problems. It is always recommended to test new algorithms on complex optimization problems. UC is one of the complex power system optimization problems. Hence, we validated the performance of GBO on UC. GBO proved good balance between exploitation and exploration and chances of getting trapped in the local optima is always rare in GBO. So, it can be suggested that GBO is one of the candidate algorithms for solving complex optimization problems such as UC.

In the electrical power production, the problem of unit commitment (UC) represents a big family of the mathematical optimization problems. In this regard, producing electrical generators set is coordinated to realize some common target, commonly either matching the demand of energy at minimal

TABLE 1. Review of research works on unit commitment.

Ref.	Year	Diligence	Algorithm
[1]	2018	Two updated version of GWO for solving unit commitment	GWO
[2]	2018	Hybridization of GA with MILP for solving unit commitment in a microgrid environment	Hybrid GA MILP
[3]	2019	Unit commitment of a CHP plant having cogeneration in a multi-objective framework with total operating cost and net emission as objective functions	PSO
[4]	2018	Robust formulation of unit commitment problem considering hydropower and solar	CSA
[5]	2019	A novel BWA for analyzing profit-based the UC in competitive power market	BWA
[6]	2018	Novel SCA for solving the UC of thermal units	SCA
[7]	2018	Novel PVS algorithm for solving the UC of thermal units in attendance of PHEVs	PVS
[8]	2017	Novel BASA for solving the UC in attendance of pumped storage and renewable sources	BASA
[9]	2019	Hybrid DA PSO method for solving the UC problem	DA PSO
[10]	2019	Forceful generation scheduling of thermal power plant by SCA	SCA
[11]	2020	Novel BMFO-SIG for solving unit commitment of a conventional power plant with and without wind resources	BMFO-SIG
[12]	2021	Validation of the performance of BFMO on unit commitment problem	BFMO
[13]	2019	Novel PSA algorithm for unit commitment problem	PSA
[14]	2021	Improved version of PSO for solving unit commitment in a micro grid environment in presence of battery energy storage	Improved PSO
[15]	2018	Binary CSA for solving unit commitment of a 4 unit system	Binary CSA
[16]	2021	BGSA for solving constrained unit commitment problem	BGSA
[17]	2017	Hybrid HS random search for solving unit commitment	HS Random search
[18]	2017	Quantum inspired GSA for solving the UC problem	Quantum Inspired GSA
[19]	2021	Use of BWA for analyzing profit-based UC in a smart city platform	BWA
[20]	2018	Hybridization of GA and DE for solving basic UC problem	GA DE
[21]	2021	Modelling of unit commitment problem considering line outages in case of natural calamities and using machine learning approach for its solution	Machine learning
[22]	2021	Modelling of unit commitment for hydropower plants considering multiple hydraulic head by nested optimization approach	Nested optimization approach
[23]	2021	Modelling of unit commitment as Markov process and solving it by reinforcement learning	Reinforcement learning
[24]	2021	A novel Bayesian optimization approach for unit commitment	Bayesian optimization
[25]	2021	Modelling and solution of security constrained scenario based unit commitment by considering battery energy storage	Deep learning
[26]	2021	Modelling of unit commitment considering hydropower for Quebec, Canada	Mixed Integer Linear programming
[27]	2021	Modelling of unit commitment considering random generation of wind power	Mixed Integer Linear programming
[28]	2021	Modelling of price based stochastic unit commitment and solved the same by Benders decomposition	Benders decomposition
[29]	2021	Novel polar bear optimization for scalable unit commitment problem	Polar bear optimization
[30]	2021	Modelling of scalable security-constrained unit commitment under uncertainty via Cone Programming Relaxation	Cone programming

cost or maximizing the electricity production revenue. The main properties of UC problem are:

- The units number can be large (e.g., hundreds or thousands)
- There are many kinds of units, which significantly differ in energy production costs as well as the constraints on how power is produced.
- The generation is distributed over vast geographical area, e.g., a country, and thus the electrical grid response, itself a highly complicated system, has to be considered: even if production levels for all the units are known, inspecting whether the load could be sustained, and the losses that require highly complicated power flow computations.

Thus, the unit commitment is a complex power system optimization problem having a number of decision variables and is nonlinear in nature. The nonlinear, complex, multi-variable, constrained nature of the problem makes it worth investigating.

GBO is a novel algorithm that has been validated on benchmark problems in existing research works. Motivated by the superior performance of GBO on a number of problems, this work validates its performance on UC problem. Moreover, good balance between exploration and exploitation, less probability of getting stuck in local optima makes GBO a good candidate for validating UC.

In this work, a novel Gradient Based Optimizer (GBO) is applied for solving the problem of UC. GBO is a technique roused by the Newton method including Gradient Search Rule (GSR) and Local Escaping Operator (LEO). In recent years, GBO is used in solving a number of real-world problems such as parameter extraction of photovoltaic models [31], [32] structural optimization problems [33], economic load dispatch [34], feature selection [35], coordination of overcurrent relay [36], charging station placement [37] and design of wind cube [38]. The contributions of this work are:

- Solution of unit commitment problem for five systems of 4-unit, 10-unit system, 20-unit system, 40-unit system and 100-unit system.
- Novel GBO based solution methodology for UC problem.
- Comparison of the performance of GBO with other metaheuristics such as differential evolution, Enhanced Genetic Algorithm, Lagrangian Relaxation, Genetic Algorithm, Ionic Bond-direct Particle Swarm Optimization and Bacteria Foraging Algorithm on UC problem.
- The convergence and robustness curves are performed for all used techniques.

II. PROBLEM FORMULATION

The UC issue is a famous power system optimization issue [39]. Minimizing the total cost of generation is the main objective of UC issue, that is achieved by stating the ON/OFF period of all units used in the generation system according to the constraints [39], [40]. The objective functions and constraints of UC are elaborated in this section. The fitness function involves minimization of fuel cost and startup cost [39].

The UC fitness function is the fuel cost of unit j that is characterized as a quadratic power function at time t as in Eq. (1),

$$F_j\left(P_{j,t}\right) = a_j + b_j P_{j,t} + c_j P_{j,t}^2 \tag{1}$$

where, $F_j\left(P_{j,t}\right)$ is the j^{th} unit fuel cost. c_j, b_j, and a_j are the cost factors, $P_{j,t}$ is the j^{th} unit real power output.

The total cost comprises of start-up cost, that characterizes the cost of regenerating a de-committed unit. This function is dependent on the hours of unit that has been down as in Eq. (2),

$$SU_{j,t} = \begin{cases} HSC_j & if\ T_j^{down} \leq T_{j,t}^{off} + T_j^{cold} \\ CSC_j & if\ T_{j,t}^{off} > T_j^{down} + T_j^{cold} \end{cases} \tag{2}$$

where, $SU_{j,t}$ is the unit j startup cost, HSC_j and CSC_j are the unit j hot start and the unit j cold start cost respectively, T_j^{down} is the unit j down time, T_j^{cold} is the unit j cold start hours, $T_{j,t}^{off}$ is the unit j continuous OFF time.

The UC problem is solved in accordance to a number of constraints as shown in Eq. (3) to Eq. (7),

$$u_{j,t} P_j^{min} \leq P_{j,t} \leq u_{j,t} P_j^{max} \tag{3}$$

where, P_j^{max} and P_j^{min} are the maximum and minimum power generation boundaries of unit j, $U_{j,t}$ is the ON/OFF status of j^{th} unit.

$$\sum\nolimits_{j=1}^{N} P_{j,t} u_{j,t} = PD_t \tag{4}$$

where, PD_t is the total demand of the system at time t.

$$\sum\nolimits_{j=1}^{N} P_j^{max} u_{j,t} \geq PD_t + SR_t \tag{5}$$

where, SR_t is the spinning reserve of the system at time t.

$$T_{j,t}^{on} \geq T_j^{up} \tag{6}$$

$$T_{j,t}^{off} \geq T_j^{down} \tag{7}$$

III. GRADIENT-BASED OPTIMIZER (GBO)

As of late, the GBO is a new meta-heuristic technique, which mirrors the gradient and populace based strategies together [31]–[38], [41]. In the GBO, so as to investigate the search space using a bunch of vectors as well as two fundamental factors such as the GSR and the LEO, Newton's technique is used to indicate the search direction. Principle cycle of the GBO is as per the following,

A. INITIALIZATION PROCESS

The likelihood rate and the control boundaries α in the GBO are utilized to adjust and change from exploration into exploitation. Moreover, the populace size and emphasis numbers are because of the issue's complexity. The search space D-dimensional in the GBO algorithm can be characterized as,

$$X_{n,d} = \left[X_{n,1}, X_{n,2}, \ldots X_{n,D}\right], \quad n = 1, 2, \ldots N;\ d = 1, 2 \ldots D \tag{8}$$

Generally, the initial vectors from GBO are randomly produced in the D-variable search area, which can be characterized as,

$$X_n = X_{min} + \text{rand}\,(0, 1)\,.\,(X_{max} - X_{min}) \tag{9}$$

where, X_{max} and X_{min} are the decision parameters boundaries.

B. PROCESS OF GSR

In the GBO calculation, to ensure a harmony between exploration of critical search area and exploitation to move close to ideal and worldwide focuses, an important factor ρ_1 is utilized as follows,

$$\rho_1 = 2.\text{rand}.\alpha - \alpha \tag{10}$$

$$\propto = \left|\beta \sin\left(\frac{3\pi}{2} + \sin\left(\beta \times \frac{3\pi}{2}\right)\right)\right| \tag{11}$$

$$\beta = \beta_{min} + (\beta_{max} - \beta_{min})\,.\left(1 - \left(\frac{m}{M}\right)^3\right)^2 \tag{12}$$

TABLE 2. Description of 4-unit system [39].

Unit	P^{max} (MW)	P^{min} (MW)	a ($/hr)	b ($/MWhr)	c ($/MW ^{2}hr)	Min up (hr)	Min down (hr)	Hot start cost ($)	Cold start cost ($)	Cold start hour (hr)	Initial status
1	80	25	213	20.74	0.0018	2	4	150	350	4	80
2	250	60	585.62	16.95	0.0042	3	5	170	400	5	8
3	300	75	648.74	16.83	0.0021	4	5	500	1100	5	8
4	60	20	252	23.60	0.0034	1	1	0	0.02	0	−6

TABLE 3. Description of 10-unit system [39].

Unit	P^{max} (MW)	P^{min} (MW)	a ($/hr)	b ($/MWhr)	c ($/MW ^{2}hr)	Min up (hr)	Min down (hr)	Hot start cost ($)	Cold start cost ($)	Cold start hour (hr)	Initial status
1	455	150	1000	16.19	0.00048	8	8	4500	9000	5	8
2	455	150	970	17.26	0.00031	8	8	5000	10000	5	8
3	130	20	700	16.60	0.00200	5	5	550	1100	4	−5
4	130	20	680	16.50	0.00211	5	5	560	1120	4	−5
5	162	25	450	19.70	0.00398	6	6	900	1800	4	−6
6	80	20	370	22.26	0.00712	3	3	170	340	2	−3
7	85	25	480	27.74	0.00079	3	3	260	520	2	−3
8	55	10	660	25.92	0.00413	1	1	30	60	0	−1
9	55	10	665	27.27	0.00222	1	1	30	60	0	−1
10	55	10	670	27.79	0.00173	1	1	30	60	0	−1

TABLE 4. Load pattern of 4-unit system [39].

Hour	Load (MW)
8	500
7	290
6	280
5	400
4	540
3	600
2	530
1	450

where, the values of β_{max} and β_{min} are 1.2 and 0.2, respectively, while m addresses the number of iteration, and M addresses the all-out iterations. Especially, the ρ_1 parameter is liable for adjusting the exploration and exploitation dependent on the sine function α. The GSR can be defined as follows,

$$\mathrm{GSR} = \mathrm{randn}.\rho_1.\frac{2\Delta \mathrm{x}.\mathrm{x_n}}{\mathrm{x_{worst}} - \mathrm{x_{best}} + \varepsilon} \tag{13}$$

The idea of GSR is to give the GBO technique an irregular conduct through iterations, in this manner reinforcing exploration conduct and departure from native optima. In Eq. (13), it is characterized by the factor Δx that conveys the distinction between the best $\mathrm{x_{best}}$ and a haphazardly selected $\mathrm{x^m_{r1}}$. The boundary δ is changed throughout cycles because of Eq. (16). Also, the exploration is improved using a random number *randn* as follows,

$$\Delta \mathrm{x} = \mathrm{rand}(1:\mathrm{N}).\,|\mathrm{step}| \tag{14}$$

$$\mathrm{step} = \frac{\left(\mathrm{x_{best}} - \mathrm{x^m_{r1}}\right) + \delta}{2} \tag{15}$$

$$\delta = 2.rand.\left(\frac{\left|x^m_{r1} + x^m_{r2} + x^m_{r3} + x^m_{r4}\right|}{4} - x^m_n\right) \tag{16}$$

where, the values of rand(1 : N) $\in$ [0, 1]. Also, four arbitrary integer numbers are looked over [1, N], which are $\mathrm{r_1}$, $\mathrm{r_2}$, $\mathrm{r_3}$, and $\mathrm{r_4}$ such that $\mathrm{r_4} \neq \mathrm{r_3} \neq \mathrm{r_2} \neq \mathrm{r_1} \neq \mathrm{n}$, and the variable step signifies a stage size which is controlled by $\mathrm{x^m_{r1}}$ and $\mathrm{x_{best}}$.

In addition, Direction Development (DM) is utilized to unite around the solution region $\mathrm{x_n}$. To furnish an advantageous neighborhood search propensity with a important impact on the convergence of GBO, the term DM can be identified as follows,

$$\mathrm{DM} = \mathrm{rand}.\rho_2.\left(\mathrm{x_{best}} - \mathrm{x_n}\right) \tag{17}$$

where, the value of rand variable is randomly range $\in$ [0, 1], and ρ_2 is an irregular parameter utilized to alter step size. The

TABLE 5. Pattern load of 10-unit system [39].

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800

TABLE 6. Comparison between GBO, IBPSO, DE and BFA on unit commitment for 4-unit system.

Algorithm	Best ($)	Worst ($)	Mean($)
IBPSO	74543	75989	75310
DE	74543	75976	75282
BFA	74651	76431	75558
GBO	74379	74877	74587

ρ_2 parameter is calculated as follows,

$$\rho_2 = 2.\text{rand}.\alpha - \alpha \tag{18}$$

Finally, based on the DM and GSR, Eqs. (13) and (17) are used to renew the position of current vector x_n^m.

$$X1_n^m = x_n^m - GSR + DM \tag{19}$$

where, $X1_n^m$ is the novel vector based on updating x_n^m. According to Eqs. (13) and (17), $X1_n^m$ can be calculated as,

$$X1_n^m = x_n^m - randn.\rho_1.\frac{2\Delta x.x_n^m}{yp_n^m - yq_n^m + \varepsilon} + randn.\rho_2.\left(x_{best} - x_n^m\right) \tag{20}$$

where, yq_n^m and yp_n^m are equal to $y_n - \Delta x$ and $y_n + \Delta x$, respectively, and y_n is the average vector for the current solution vector x_n and the vector z_{n+1} that are computed as follows,

$$z_{n+1} = x_n - randn.\frac{2\Delta x.x_n}{x_{worst} - x_{best} + \varepsilon} \tag{21}$$

while, the best and worst solution are x_{best}andx_{worst} respectively, and Δx is given by equation 14. Based on this equation, when replacing the vector of best solution x_{best} with the vector of current solution x_n^m, we get $X2_n^m$ as follows,

$$X2_n^m = x_{best} - \text{randn}.\rho_1.\frac{2\Delta x.x_n^m}{yp_n^m - yq_n^m + \varepsilon} + \text{randn}.\rho_2.\left(x_{r1}^m - x_{r2}^m\right) \tag{22}$$

In particular, the GBO method means to upgrade the exploitation and exploration stages utilizing Eq. (20) to work on the global solution for the exploration stage, while Eq. (22) is utilized to further develop the neighborhood search ability for the exploitation stage. At last, the solution of the subsequent iteration is as per the following,

$$x_n^{m+1} = r_a.\left(r_b.X1_n^m + (1-r_b).X2_n^m\right) + (1-r_\alpha).X3_n^m \tag{23}$$

where, the value of r_b and r_a are ranged from 0 to 1, and $X3_n^m$ is calculated as follow,

$$X3_n^m = X_n^{m+1} - \rho_1.\left(X2_n^m - X1_n^m\right) \tag{24}$$

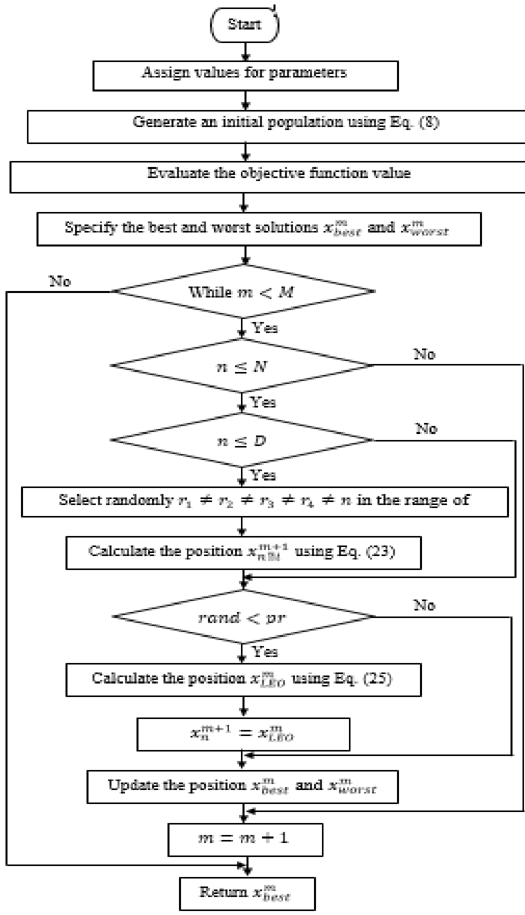

FIGURE 1. GBO flow chart.

C. PROCESS OF LEO

The LEO is acquainted with reinforce the GBO algorithm performance to take care of intricate issues. The LEO can adequately refresh the solution position, to help a technique to leave nearby optima focuses and speed up convergence of the improvement method. The LEO aims create a new result with superior performance X_{LEO}^m by numerous solutions to renew the current solution. The following structure is used to act this process,

If rand $<$ pr

$$X_{LEO}^m = \begin{cases} X_n^{m+1} + f_1\left(u_1 x_{best} - u_2 x_k^m\right) + f_2\rho_1\left(u_3\left(X2_n^m - X1_n^m\right) + u_2\left(x_{r1}^m - x_{r2}^m\right)\right)/2, & \text{if rand } < 0.5 \\ x_{best} + f_1\left(u_1 x_{best} - u_2 x_k^m\right) + f_2\rho_1\left(u_3\left(X2_n^m - X1_n^m\right) + u_2\left(x_{r1}^m - x_{r2}^m\right)\right)/2, & \text{otherwise} \end{cases}$$

End (25)

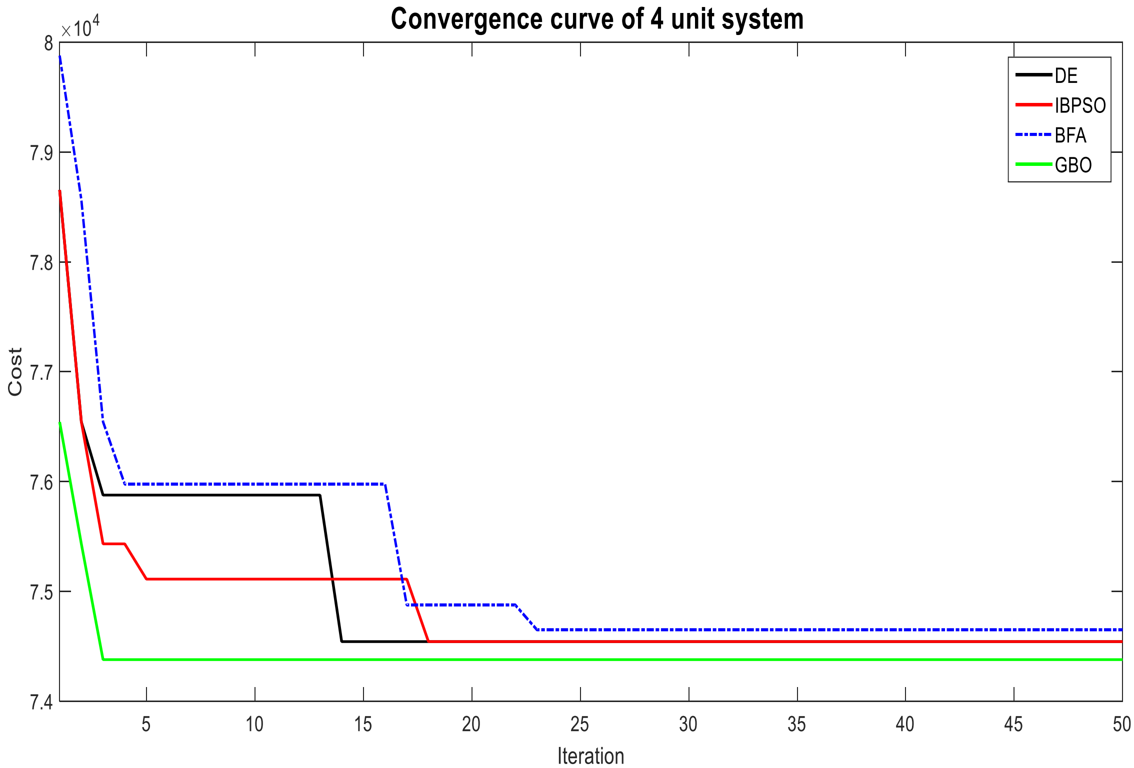

FIGURE 2. Convergence curve for 4-unit system.

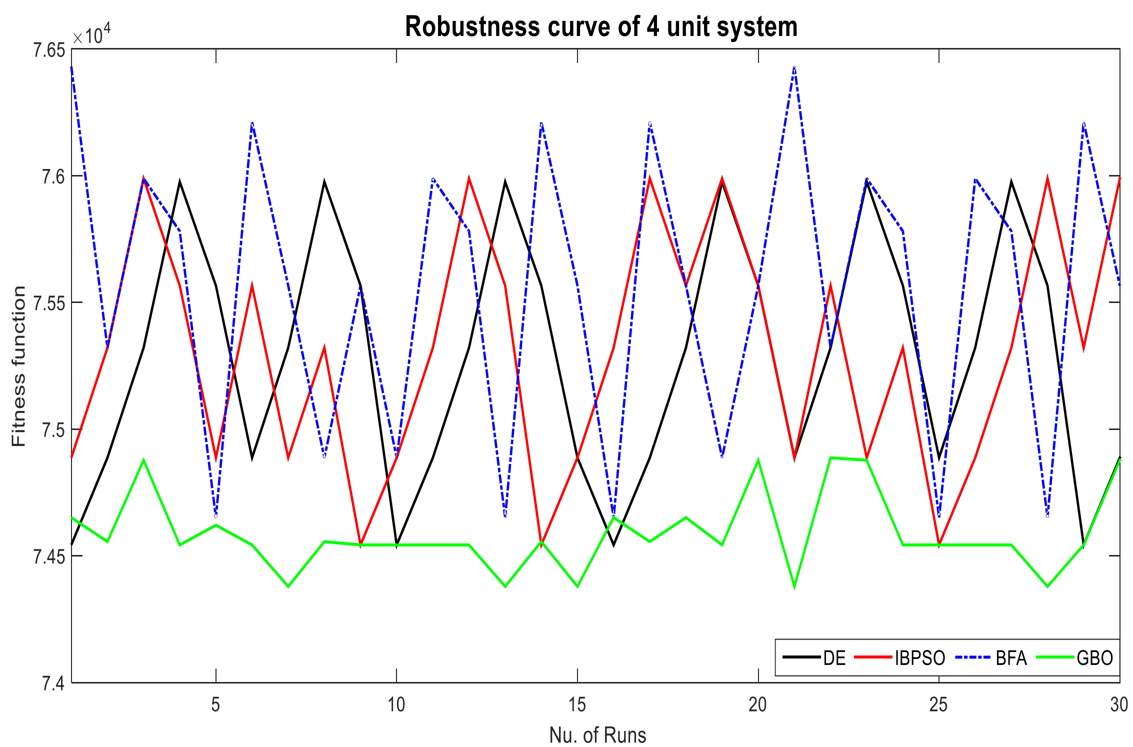

FIGURE 3. Robustness curve for 4-unit system.

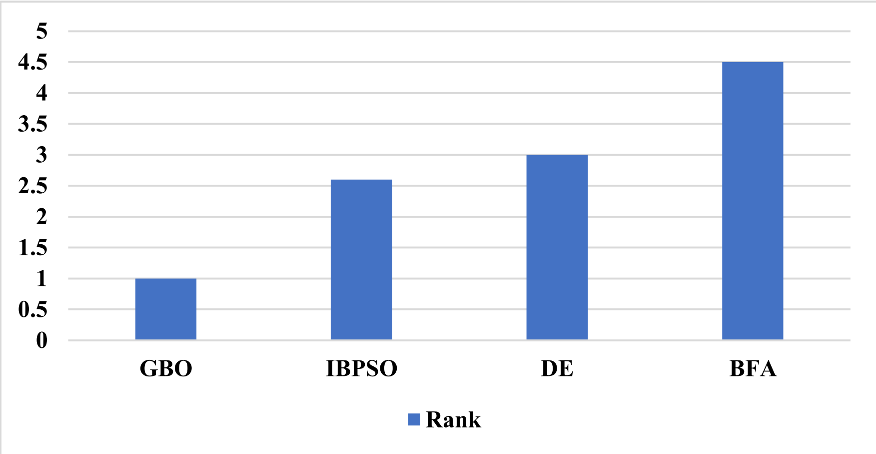

FIGURE 4. Friedman rank test result for 4-unit system.

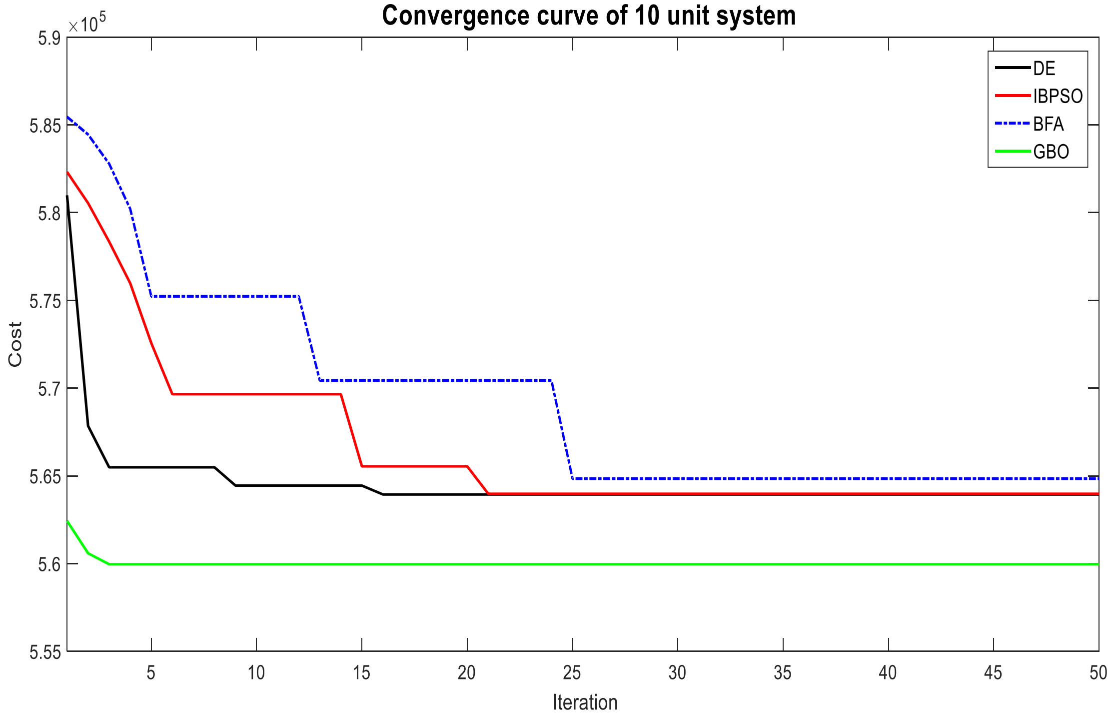

FIGURE 5. Convergence curve for 10-unit system.

where, the value of pr is 0.5, f_1 and f_2 are random numbers with uniform distribution $\in [-1, 1]$, and the value of u_1, u_2 and u_3 are created as follows,

$$u_1 = \begin{cases} 2.\text{rand}, & \text{if } \mu_1 < 0.5 \\ 1, & \text{otherwise} \end{cases} \tag{26}$$

$$u_2 = \begin{cases} \text{rand}, & \text{if } \mu_1 < 0.5 \\ 1, & \text{otherwise} \end{cases} \tag{27}$$

$$u_3 = \begin{cases} \text{rand}, & \text{if } \mu_1 < 0.5 \\ 1, & \text{otherwise} \end{cases} \tag{28}$$

where, the value of μ_1 is in range [0, 1]. The equations for u_3, u_2 and u_1 can be justified as follow,

$$u_1 = L_1.2.\text{rand} + (1-L_1) \tag{29}$$

$$u_2 = L_1.\text{rand} + (1-L_1) \tag{30}$$

$$u_3 = L_1.\text{rand} + (1-L_1) \tag{31}$$

where, the value of L_1 is a binary number 0 or 1. The solution x_k^m is produced as follows,

$$x_k^m = \begin{cases} x_{\text{rand}}, & \text{if } \mu_2 < 0.5 \\ x_p^m, & \text{otherwise} \end{cases} \tag{32}$$

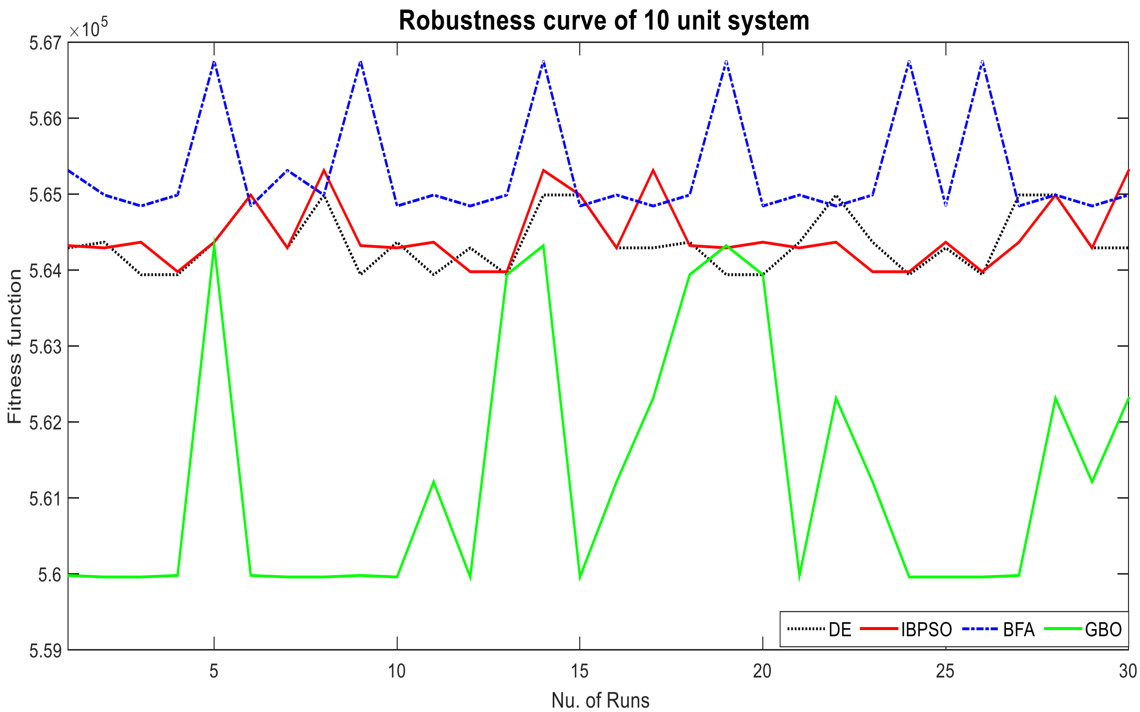

FIGURE 6. Robustness curve for 10-unit system.

TABLE 7. Optimal generation scheduling in MW of 4-unit system obtained by GBO.

Unit	Hour							
	1	2	3	4	5	6	7	8
1	0	25	30	25	0	0	0	0
2	150	205	250	215	123.8095	83.8095	87.1429	200
3	300	300	300	300	276.1905	196.1905	202.8571	300
4	0	0	20	0	0	0	0	0

TABLE 8. Comparison between GBO, IBPSO, DE and BFA on unit commitment for 10-unit system.

Algorithm	Best ($)	Worst($)	Mean ($)
IBPSO	563977	565312	564450
DE	563938	564987	564360
BFA	564842	566754	565312
GBO	559960	564321	561280

where, the solution, x_{rand} is random according to the following formula and x_p^m is a randomly solution, the value of μ_2 is $\in [0, 1]$.

$$x_{rand} = X_{min}.rand(0, 1).(X_{max} - X_{min}) \tag{33}$$

The proposed algorithm is described in the flow chart of figure 1.

IV. NUMERICAL ANALYSIS

A. TEST SYSTEM

The UC problem is solved for 10-unit and 4-unit system. The details of the aforementioned test systems are as shown in Table 2 and Table 3. The load pattern of 10-unit and 4-unit system are as shown in Table 4 and Table 5 respectively.

B. COMPARISON OF GBO WITH DE, IBPSO, BFA ON UNIT COMMITMENT PROBLEM

The performance of GBO on Unit Commitment problem is compared with DE, IBPSO, and BFA for 4-unit as well as 10-unit system. The results of that comparison are presented in this section. Table 6 illustrates the best, worst, and mean cost achieved by IBPSO, DE, BFA, and GBO in case of 4-unit test system. Based on that the GBO performance is better than the other state-of-art algorithms for this case study. The best cost yielded by GBO is 74379 $ which is less as compared to other algorithms. The optimal generation scheduling in MW of 4-unit system obtained by GBO is reported in Table 7. The convergence curve in case of 4-unit system is as shown in Fig.2. The X axis of the convergence curve is iteration, and the Y axis is mean cost in $ as depicted in section II. Based on that GBO favors faster convergence as competed to other algorithms.

Metaheuristic algorithms are stochastic in nature that are designed to operate on discrete variable spaces utilize randomness and memory to search large discrete variable spaces in order to find an optimal solution. Hence, it is required to investigate how robust the algorithm is. Robustness curve signifies the variation of fitness function with number of runs.

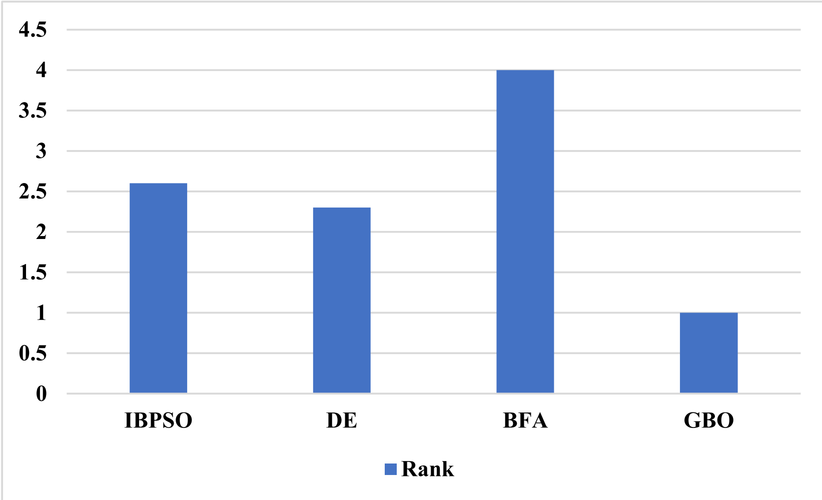

FIGURE 7. Friedman rank test results for 10-unit system.

TABLE 9. Optimal generation scheduling in MW of 10-unit system obtained by GBO.

Time	Unit 10	Unit 9	Unit 8	Unit 7	Unit 6	Unit 5	Unit 4	Unit 3	Unit 2	Unit 1
1	0	0	0	0	0	0	0	0	245	455
2	0	0	0	0	0	0	0	0	295	455
3	0	0	0	0	0	25	0	0	370	455
4	0	0	0	0	0	40	0	0	455	455
5	0	0	0	0	0	25	0	130	390	455
6	0	0	0	0	0	25	130	130	360	455
7	0	0	0	0	0	25	130	130	410	455
8	0	0	0	0	0	30	130	130	455	455
9	0	0	0	25	20	85	130	130	455	455
10	0	0	10	25	33	162	130	130	455	455
11	0	10	10	25	73	162	130	130	455	455
12	10	10	43	25	80	162	130	130	455	455
13	0	0	10	25	33	162	130	130	455	455
14	0	0	0	25	20	85	130	130	455	455
15	0	0	0	0	0	30	130	130	455	455
16	0	0	0	0	0	25	130	130	310	455
17	0	0	0	0	0	25	130	130	260	455
18	0	0	0	0	0	25	130	130	360	455
19	0	0	0	0	0	30	130	130	455	455
20	0	10	0	25	33	162	130	130	455	455
21	0	0	0	25	20	85	130	130	455	455
22	0	0	0	25	20	145	0	0	455	455
23	0	0	0	0	20	0	0	0	425	455
24	0	0	0	0	0	0	0	0	345	455

Fig. 3 shows the robustness curve in case of 4-unit system. Based on this figure, the robustness of GBO is more as compared to other algorithms. Further, Friedman rank test is conducted and the Friedman rank test results are reported in Fig. 4. Based on this figure, the best rank achieved by GBO then IBPSO.

Table 8 illustrates the best, worst, and mean cost obtained by IBPSO, DE, BFA, and GBO in case of 10-unit test system. Based on the GBO performance is better than the other state-of-art algorithms for this case study. The best cost yielded by GBO is 559960$ which is less as compared to other algorithms. The optimal generation scheduling in MW of 10-unit system obtained by GBO is reported in Table 9. The convergence curve in case of 10-unit system is as shown in Fig.5. The X axis of the convergence curve is iteration, and the Y axis is mean cost in $ as depicted in section II. Accordingly, GBO favors faster convergence as competed to other algorithms. Also, the possibility of getting stuck in local optima is rare in case of GBO. Fig. 6 shows the robustness curve in case of 10-unit system. Based on that, the robustness of GBO is more as compared to other algorithms. Further, Friedman rank test is conducted and the Friedman rank test results are reported in Fig. 7. The Friedman Test is a statistical test used to determine if 3 or more measurements

TABLE 10. Comparison of GBO with LR, GA, and EGA on unit commitment for 4-unit system.

Algorithm	Best ($)
LR	76975.33
GA	77628.91
EGA	77628.91
GBO	74379

TABLE 11. Comparison of GBO with LR, GA, and EGA on unit commitment for 10-unit system.

Algorithm	Best ($)
LR	565673. 13
GA	564217.08
EGA	563937.57
GBO	559960

TABLE 12. Comparison of GBO with LR, PSO LR, GA, BCGA, BF on unit commitment for large test systems.

Unit	Algorithm	Best ($)
20	LR	1130660
	PSO LR	1128072
	GA	1126243
	BCGA	1130291
	BF	1128112
	BGWO	1126126.3
	GBO	1123607
40	LR	2258503
	PSO LR	2251116
	GA	2251911
	BCGA	2256590
	BF	2255112
	BGWO	2257866.7
	GBO	2250968
100	LR	5657277
	PSO LR	5623607
	GA	5627437
	BCGA	5637930
	BF	5632491
	BGWO	5637659
	GBO	5605933

from the same group of subjects are significantly different from each other on a skewed variable of interest. The variable of interest should be continuous, and have a similar spread across the groups. The algorithm that performs best i.e have least significant difference is the one having the lowest rank. Accordingly, the best rank has been achieved by GBO then DE.

C. COMPARISON OF GBO WITH LR, GA, EGA ON UNIT COMMITMENT PROBLEM

The performance of GBO is compared with LR, GA, EGA on UC problem for 10-unit and 4-unit system. The unit commitment problem is solved with GBO and its performance is compared with LR, GA, and EGA. The solution of unit commitment by LR, GA, and EGA is utilized from ref [41]. And, the GBO solve the UC problem with the same parameter settings as in ref [41]. Table 10 reports the results of GBO, LR, GA, EGA on UC problem for 4-unit system. Based on this table, the performance of GBO is superior visible compared with others algorithm. Table 11 reports the best cost obtained by GBO, LR, GA, and EGA in case of 10-unit system. Based on this table, GBO performance is better than LR, GA, and EGA.

TABLE 13. Comparison time complexity of GBO with other metaheuristics.

Algorithm	Avg Run time (sec)
GBO	12.45
DE	15.12
BFA	20.56
IBPSO	19.22

D. COMPARISON OF GBO WITH OTHER STATE OF ART ALGORITHMS ON UNIT COMMITMENT PROBLEM FOR LARGE TEST SYSTEMS

The performance of GBO is compared with other metaheuristics such as LR, PSO LR, GA, BCGA, BF on UC problem for larger test systems. The solution of unit commitment by LR, PSO LR, GA, BCGA, BF is utilized from ref [42]. And the GBO is used to solve the UC problem with the same parameter settings as in ref [42]. Table 12 reports the results of LR, PSO LR, GA, BCGA, BF on UC problem for 20, 40, and 100-unit system. Based on this table, the performance of GBO is superior visible compared with others algorithm.

E. TIME COMPLEXITY ANALYSIS

The 4-unit test system is considered as a test case for comparing the time complexity of GBO with other metaheuristics. Table 13 reports the average run time of GBO, DE, BFA, IBPSO for the 4 unit system. It is observed that GBO performs better than the others

V. CONCLUSION

Electric power system has one of the mixed-integer and nonlinear problems, that is called unit commitment (UC). UC is one of the complex optimization tasks performed by power plant engineers for regular planning and operation of power system. Researchers have used a number of metaheuristics (MH) for solving this complex and demanding problem. The performance of novel GBO algorithm on unit commitment problem is tested in this work. It is observed that the GBO performance is competitive as competed to other state-of-art algorithms. For 4-unit system, best cost yielded by GBO is 74379 $ which is less as compared to other algorithms. For 10-unit system, the best cost yielded by GBO is 559960$ which is less as competed to other algorithms. Additionally, it is checked that GBO has obtained the best rank as competed to other algorithms. For large unit systems it is observed that GBO yields relatively better results. GBO has well balance between exploitation and exploration. Also, the probability of getting caught in local optima and early convergence is rare in GBO. Our future work will focus on:

- Hybridization of GBO with other metaheuristics
- Solution of unit commitment problem in presence of renewable sources and Electric Vehicles as storage
- Performance validation of GBO on other complex and demanding power system optimization problem.

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REFERENCES

[1] L. K. Panwar, S. Reddy K, A. Verma, B. K. Panigrahi, and R. Kumar, ''Binary grey wolf optimizer for large scale unit commitment problem,'' *Swarm Evol. Comput.*, vol. 38, pp. 251–266, Feb. 2018.

[2] M. Nemati, M. Braun, and S. Tenbohlen, ''Optimization of unit commitment and economic dispatch in microgrids based on genetic algorithm and mixed integer linear programming,'' *Appl. Energy*, vol. 210, pp. 944–963, Jan. 2018.

[3] H. Anand, N. Narang, and J. S. Dhillon, ''Multi-objective combined heat and power unit commitment using particle swarm optimization,'' *Energy*, vol. 172, pp. 794–807, Apr. 2019.

[4] B. Ming, P. Liu, S. Guo, L. Cheng, Y. Zhou, S. Gao, and H. Li, ''Robust hydroelectric unit commitment considering integration of large-scale photovoltaic power: A case study in China,'' *Appl. Energy*, vol. 228, pp. 1341–1352, Oct. 2018.

[5] S. K. Reddy, L. Panwar, B. K. Panigrahi, and R. Kumar, ''Binary whale optimization algorithm: A new metaheuristic approach for profit-based unit commitment problems in competitive electricity markets,'' *Eng. Optim.*, vol. 51, pp. 369–389, May 2018.

[6] L. M. de Oliveira, F. F. Panoeiro, I. C. D. S. Junior, and L. W. Oliveira, ''Application of the sine cosine optimization algorithm for thermal unit commitment,'' in *Proc. Simposio Brasileiro de Sistemas Eletricos (SBSE)*, May 2018, pp. 1–6.

[7] A. Kumar, M. Bhadu, and S. K. Bishnoi, ''Constrained unit commitment based power generation dispatching with integration of PHEVs,'' in *Proc. 8th IEEE India Int. Conf. Power Electron. (IICPE)*, Dec. 2018, pp. 1–6.

[8] W. Wang, C. Li, X. Liao, and H. Qin, ''Study on unit commitment problem considering pumped storage and renewable energy via a novel binary artificial sheep algorithm,'' *Appl. Energy*, vol. 187, pp. 612–626, Feb. 2017.

[9] S. Khunkitti, N. R. Watson, R. Chatthaworn, S. Premrudeepreechacharn, and A. Siritaratiwat, ''An improved DA-PSO optimization approach for unit commitment problem,'' *Energies*, vol. 12, no. 12, p. 2335, Jun. 2019.

[10] A. Bhadoria, S. Marwaha, and V. K. Kamboj, ''An optimum forceful generation scheduling and unit commitment of thermal power system using sine cosine algorithm,'' *Neural Comput. Appl.*, vol. 32, no. 7, pp. 2785–2814, 2019.

[11] A. Bhadoria, S. Marwaha, and V. K. Kamboj, ''BMFO-SIG: A novel binary moth flame optimizer algorithm with sigmoidal transformation for combinatorial unit commitment and numerical optimization problems,'' *Trans. Indian Nat. Acad. Eng.*, vol. 5, no. 4, pp. 789–826, Dec. 2020.

[12] J.-S. Pan, P. Hu, and S.-C. Chu, ''Binary fish migration optimization for solving unit commitment,'' *Energy*, vol. 226, Jul. 2021, Art. no. 120329.

[13] C. Chitra and T. Amudha, ''Optimal unit commitment for thermal power systems using penguin search algorithm,'' in *Proc. Int. Conf. Emerg. Trends Eng.*, 2019, pp. 581–591.

[14] A. R. Jordehi, ''An improved particle swarm optimisation for unit commitment in microgrids with battery energy storage systems considering battery degradation and uncertainties,'' *Int. J. Energy Res.*, vol. 45, no. 1, pp. 727–744, Jan. 2021.

[15] J. Zhao, S. Liu, M. Zhou, X. Guo, and L. Qi, ''An improved binary cuckoo search algorithm for solving unit commitment problems: Methodological description,'' *IEEE Access*, vol. 6, pp. 43535–43545, 2018.

[16] M. Shahid, T. N. Malik, and A. Said, ''Heuristic based binary grasshopper optimization algorithm to solve unit commitment problem,'' *TURKISH J. Electr. Eng. Comput. Sci.*, vol. 29, no. 2, pp. 944–961, Mar. 2021.

[17] V. K. Kamboj, S. K. Bath, and J. S. Dhillon, ''Hybrid HS–random search algorithm considering ensemble and pitch violation for unit commitment problem,'' *Neural Comput. Appl.*, vol. 28, no. 5, pp. 1123–1148, May 2017.

[18] F. Barani, M. Mirhosseini, H. Nezamabadi-Pour, and M. M. Farsangi, ''Unit commitment by an improved binary quantum GSA,'' *Appl. Soft Comput.*, vol. 60, pp. 180–189, Nov. 2017.

[19] M. Elkamel, A. Ahmadian, A. Diabat, and Q. P. Zheng, ''Stochastic optimization for price-based unit commitment in renewable energy-based personal rapid transit systems in sustainable smart cities,'' *Sustain. Cities Soc.*, vol. 65, Feb. 2021, Art. no. 102618.

[20] J. S. Dhaliwal and J. S. Dhillon, ''Modified binary differential evolution algorithm to solve unit commitment problem,'' *Electr. Power Compon. Syst.*, vol. 46, no. 8, pp. 900–918, May 2018.

[21] F. Mohammadi, M. Sahraei-Ardakani, D. Trakas, and N. Hatziargyriou, ''Machine learning assisted stochastic unit commitment during hurricanes with predictable line outages,'' *IEEE Trans. Power Syst.*, vol. 36, no. 6, pp. 5131–5142, Nov. 2021.

[22] Q. Cheng, B. Ming, P. Liu, K. Huang, Y. Gong, X. Li, and Y. Zheng, ''Solving hydro unit commitment problems with multiple hydraulic heads based on a two-layer nested optimization method,'' *Renew. Energy*, vol. 172, pp. 317–326, Jul. 2021.

[23] P. de Mars and A. O'Sullivan, ''Applying reinforcement learning and tree search to the unit commitment problem,'' *Appl. Energy*, vol. 302, Nov. 2021, Art. no. 117519.

[24] P. Nikolaidis and S. Chatzis, ''Gaussian process-based Bayesian optimization for data-driven unit commitment,'' *Int. J. Electr. Power Energy Syst.*, vol. 130, Sep. 2021, Art. no. 106930.

[25] T. Wu, Y.-J. A. Zhang, and S. Wang, ''Deep learning to optimize: Security-constrained unit commitment with uncertain wind power generation and BESSs,'' *IEEE Trans. Sustain. Energy*, vol. 13, no. 1, pp. 231–240, Jan. 2022.

[26] M. Daadaa, S. Séguin, K. Demeester, and M. F. Anjos, ''An optimization model to maximize energy generation in short-term hydropower unit commitment using efficiency points,'' *Int. J. Electr. Power Energy Syst.*, vol. 125, Feb. 2021, Art. no. 106419.

[27] J. Dong, S. Han, X. Shao, L. Tang, R. Chen, L. Wu, C. Zheng, Z. Li, and H. Li, ''Day-ahead wind-thermal unit commitment considering historical virtual wind power data,'' *Energy*, vol. 235, Nov. 2021, Art. no. 121324.

[28] M. Elkamel, A. Ahmadian, A. Diabat, and Q. P. Zheng, ''Stochastic optimization for price-based unit commitment in renewable energy-based personal rapid transit systems in sustainable smart cities,'' *Sustain. Cities Soc.*, vol. 65, Feb. 2021, Art. no. 102618.

[29] S. S. Ul Haq, A. Ahmad, F. Ikram, T. Nawaz, A. Majeed, M. S. Saddique, and M. K. Sattar, ''A novel binary variant model of swarm inspired polar bear optimization algorithm employed for scalable unit commitment,'' *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 2, Feb. 2021, Art. no. e12711.

[30] E. Quarm and R. Madani, ''Scalable security-constrained unit commitment under uncertainty via cone programming relaxation,'' *IEEE Trans. Power Syst.*, vol. 36, no. 5, pp. 4733–4744, Sep. 2021.

[31] A. A. K. Ismaeel, E. H. Houssein, D. Oliva, and M. Said, ''Gradient-based optimizer for parameter extraction in photovoltaic models,'' *IEEE Access*, vol. 9, pp. 13403–13416, 2021.

[32] M. H. Hassan, S. Kamel, M. A. El-Dabah, and H. Rezk, ''A novel solution methodology based on a modified gradient-based optimizer for parameter estimation of photovoltaic models,'' *Electronics*, vol. 10, no. 4, p. 472, Feb. 2021.

[33] M. Premkumar, P. Jangir, and R. Sowmya, ''MOGBO: A new multi-objective gradient-based optimizer for real-world structural optimization problems,'' *Knowl.-Based Syst.*, vol. 218, Apr. 2021, Art. no. 106856.

[34] S. Deb, D. S. Abdelminaam, M. Said, and E. H. Houssein, ''Recent methodology-based gradient-based optimizer for economic load dispatch problem,'' *IEEE Access*, vol. 9, pp. 44322–44338, 2021.

[35] Y. Jiang, Q. Luo, Y. Wei, L. Abualigah, and Y. Zhou, ''An efficient binary Gradient-based optimizer for feature selection,'' *Math. Biosci. Eng.*, vol. 18, no. 4, pp. 3813–3854, 2021.

[36] R. M. Rizk-Allah and A. A. El-Fergany, ''Effective coordination settings for directional overcurrent relay using hybrid gradient-based optimizer,'' *Appl. Soft Comput.*, vol. 112, Nov. 2021, Art. no. 107748.

[37] E. H. Houssein, S. Deb, D. Oliva, H. Rezk, H. Alhumade, and M. Said, ''Performance of gradient-based optimizer on charging station placement problem,'' *Mathematics*, vol. 9, no. 21, p. 2821, Nov. 2021.

[38] A. Abumwais, A. Amirjanov, K. Uyar, and M. Eleyat, ''Performance of gradient-based optimizer for optimum wind cube design,'' *Comput., Mater. Continua*, vol. 71, no. 1, pp. 339–353, 2022.

[39] G. B. Sheble and G. N. Fahd, ''Unit commitment literature synopsis,'' *IEEE Trans. Power Syst.*, vol. 9, no. 1, pp. 128–135, Feb. 1994.

[40] P. K. Singhal, R. Naresh, V. Sharma, and N. G. Kumar, ''Solution of unit commitment problem using enhanced genetic algorithm,'' in *Proc. 18th Nat. Power Syst. Conf. (NPSC)*, Dec. 2014, pp. 1–6.

[41] I. Ahmadianfar, O. Bozorg-Haddad, and X. Chu, ''Gradient-based optimizer: A new Metaheuristic optimization algorithm,'' *Inf. Sci.*, vol. 540, pp. 131–159, Nov. 2020.

[42] S. Najafi and Y. Pourjamal, ''A new heuristic algorithm for unit commitment problem,'' *Energy Proc.*, vol. 14, pp. 2005–2011, Jan. 2012.