A Novel Gradient Based Optimizer for Solving Unit Commitment Problem

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\textbf{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.

\textbf{INDEX TERMS} Unit commitment, power system, gradient based optimizer.

\textbf{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.
PSV - 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 BMFOSIG 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 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 PHIEVs | 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              |
| [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).

$$ F_j(P_{j,t}) = a_j + b_jP_{j,t} + c_jP_{j,t}^2 $$

where, $F_j(P_{j,t})$ 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),

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

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, $T_{j}^{\text{down}}$ is the unit $j$ down time, $T_{j}^{\text{cold}}$ is the unit $j$ cold start hours, $T_{j,t}^{\text{off}}$ 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),

$$ u_{j,t}^{\text{min}} \leq P_{j,t} \leq u_{j,t}^{\text{max}} $$

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

$$ \sum_{j=1}^{N} P_{j,t}^{u_{j,t}} = PD_t $$

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

$$ \sum_{j=1}^{N} P_{j,t}^{u_{j,t}} \geq PD_t + SR_t $$

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

$$ T_{j,t}^{\text{on}} \geq T_{j}^{\text{up}} $$

$$ T_{j,t}^{\text{off}} \geq T_{j}^{\text{down}} $$

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 $\alpha$ 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,

$$ X_{n,d} = [X_{n,1}, X_{n,2}, \ldots, X_{n,D}] $$

$$ n = 1, 2, \ldots N; d = 1, 2 \ldots D $$

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

$$ X_0 = X_{\text{min}} + \text{rand}(0, 1)(X_{\text{max}} - X_{\text{min}}) $$

where, $X_{\text{max}}$ and $X_{\text{min}}$ 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 $\rho_1$ is utilized as follows,

$$ \rho_1 = 2 \text{rand} \cdot \alpha - \alpha $$

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

$$ \beta = \beta_{\text{min}} + (\beta_{\text{max}} - \beta_{\text{min}}) \cdot \left( 1 - \frac{m}{M} \right)^2 $$
where, the values of $\beta_{\text{max}}$ and $\beta_{\text{min}}$ are 1.2 and 0.2, respectively, while $m$ addresses the number of iteration, and $M$ addresses the all-out iterations. Especially, the $\rho_1$ parameter is liable for adjusting the exploration and exploitation dependent on the sine function $\alpha$. The GSR can be defined as follows,

\[
\text{GSR} = \text{randn} \cdot \rho_1 \cdot \frac{2 \Delta x \cdot x_n}{x_{\text{worst}} - x_{\text{best}} + \varepsilon} \quad (13)
\]

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 $\Delta x$ that conveys the distinction between the best $x_{\text{best}}$ and a haphazardly selected $x_{m}$. The boundary $\delta$ is changed throughout cycles because of Eq. (16). Also, the exploration is improved using a random number $\text{rand}$ as follows,

\[
\Delta x = \text{rand}(1 : N), \, |\text{step}| \\
\text{step} = \frac{(x_{\text{best}} - x_{m}) + \delta}{2} \quad (15)
\]

\[
\delta = 2 \cdot \text{rand} \cdot \left( \frac{|x_{r_1} + x_{r_2} + x_{r_3} + x_{r_4}| - x_n}{4} \right) \quad (16)
\]

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

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

\[
\text{DM} = \text{rand} \cdot \rho_2 \cdot (x_{\text{best}} - x_n) \quad (17)
\]

where, the value of rand variable is randomly range $\in [0, 1]$, and $\rho_2$ 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|
| Load (MW) | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  | 21  | 22  | 23  | 24  |

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   |

\( \rho_2 \) parameter is calculated as follows,

\[
\rho_2 = 2 \cdot \text{rand.} \cdot \alpha - \alpha \quad (18)
\]

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

\[ X_1^n = x_n - \text{GSR} + \text{DM} \quad (19) \]

where, \( X_1^n \) is the novel vector based on updating \( x_n \). According to Eqs. (13) and (17), \( X_1^n \) can be calculated as,

\[
X_1^n = x_n - \text{rand.} \cdot \rho_1 \cdot \frac{2 \Delta x \cdot x_n}{y_p - y_q + \varepsilon} + \text{rand.} \cdot \rho_2 \cdot (x_{\text{best}} - x_n) \quad (20)
\]

where, \( y_p \) and \( y_q \) 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,

\[ z_{n+1} = x_n - \text{rand.} \cdot x_{\text{worst}} - x_{\text{best}} + \varepsilon \quad (21) \]

while, the best and worst solution are \( x_{\text{best}} \) and \( x_{\text{worst}} \) respectively, and \( \Delta x \) is given by equation 14. Based on this equation, when replacing the vector of best solution \( x_{\text{best}} \) with the vector of current solution \( x_n \), we get \( X_2^n \) as follows,

\[
X_2^n = x_{\text{best}} - \text{rand.} \cdot \rho_1 \cdot \frac{2 \Delta x \cdot x_n}{y_p - y_q + \varepsilon} + \text{rand.} \cdot \rho_2 \cdot (x_{1}^{n} - x_{2}^{n}) \quad (22)
\]

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,

\[ x_n^{m+1} = r_a \cdot (r_b \cdot X_1^n + (1-r_b) \cdot X_2^n) + (1-r_a) \cdot X_3^n \quad (23) \]

where, the value of \( r_b \) and \( r_a \) are ranged from 0 to 1, and \( X_3^n \) is calculated as follow,

\[ X_3^n = x_{n+1} - \rho_1 \cdot (X_2^n - X_1^n) \quad (24) \]

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 \( X_{\text{LEO}}^m \) by numerous solutions to renew the current solution. The following structure is used to act this process,

\[
X_{\text{LEO}}^m = \begin{cases} 
X_n^{m+1} + f_1 \left( u_1 x_{\text{best}} - u_2 X_n^m \right) + f_2 \rho_1 (u_3 X_2^n - X_1^n) + u_2 \left( x_n^{m+1} - x_n^m \right)/2, & \text{if } \text{rand} < 0.5 \\
X_{\text{best}} + f_1 \left( u_1 x_{\text{best}} - u_2 X_k^m \right) + f_2 \rho_1 (u_3 X_2^n - X_1^n) + u_2 \left( x_n^{m+1} - x_n^m \right)/2, & \text{otherwise}
\end{cases}
\]

End
**FIGURE 2.** Convergence curve for 4-unit system.

**FIGURE 3.** Robustness curve for 4-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,

\[
\begin{align*}
  u_1 &= \begin{cases} 
    2 \cdot \text{rand}, & \text{if } \mu_1 < 0.5 \\
    1, & \text{otherwise}
  \end{cases} \quad (26) \\
  u_2 &= \begin{cases} 
    \text{rand}, & \text{if } \mu_1 < 0.5 \\
    1, & \text{otherwise}
  \end{cases} \quad (27) \\
  u_3 &= \begin{cases} 
    \text{rand}, & \text{if } \mu_1 < 0.5 \\
    1, & \text{otherwise}
  \end{cases} \quad (28)
\end{align*}
\]

where, the value of \( \mu_1 \) is in range \([0, 1]\). The equations for \( u_3, u_2 \) and \( u_1 \) can be justified as follow,

\[
\begin{align*}
  u_1 &= L_1 \cdot 2 \cdot \text{rand} + (1 - L_1) \quad (29) \\
  u_2 &= L_1 \cdot \text{rand} + (1 - L_1) \quad (30) \\
  u_3 &= L_1 \cdot \text{rand} + (1 - L_1) \quad (31)
\end{align*}
\]

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

\[
\begin{align*}
  x_k^m &= \begin{cases} 
    \text{x}_{\text{rand}}, & \text{if } \mu_2 < 0.5 \\
    x_p^m, & \text{otherwise}
  \end{cases} \quad (32)
\end{align*}
\]
where, the solution, \( x_{\text{rand}} \) is random according to the following formula and \( x_{\text{mp}} \) is a randomly solution, the value of \( \mu_2 \) is \( \in [0, 1] \).

\[
x_{\text{rand}} = X_{\text{min}} \cdot \text{rand}(0, 1) \cdot (X_{\text{max}} - X_{\text{min}})
\]  

(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.
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 are statistically different from each other.
The performance of GBO is compared with LR, GA, EGA on UC problem for 10-unit and 4-unit system. 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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