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Garra Rufa Technique for Unit Commitment Optimization: A Comparative Analysis with Metaheuristic Algorithms

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ABSTRACT- Optimization techniques have received much attention in the recent years in the area of power system research. The success of any optimization process relies much on the proper choice of the algorithm and its parameters, depending on the actual problem considered. Among different approaches of optimization, Garra Rufa Optimization (GRO) has shown a great potential in the operation of power systems. This study proposes GRO for the unit commitment (UC) problem. Typically, the solution of a UC problem consists of two major stages, finding the generating units to be committed and the level of generation to be allocated among these units to minimize total operating cost while meeting load demand and system constraints. Accordingly, priority list method is applied for the first stage whereas GRO is used to optimize the second stage. To check the performance of the proposed method, a 10 generating units test system was used. The cost function values were taken as the performance indicators to compare GRO with Gray Wolf (GWO), Spider Wasp (SWO), Particle Swarm (PSO) optimization algorithms. The time for each method was calculated for 50 runs. Results for GWO, SWO, PSO, and GRO were 0.0811, 0.118, 0.0783, and 0.0793 second, respectively. Although all methods can be considered fast, GRO was the second fastest, with a slight time difference from PSO. Despite that, it is considered practically acceptable due to the noticeable improvement in the accuracy of the results. The results proves that the proposed GRO has better performance in terms of economical generator selection and least error between total generation and system demand.

Keywords: Garra Rufa, Gray Wolf, Particle Swarm Optimization, Spider Wasp, Unit Commitment.

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1. INTRODUCTION

Power systems are the core of the modern industrial society where electricity is generated, transmitted and distributed satisfying the growing domestic, commercial and industrial demand [1,2]. These networks are complicated systems, with the existence of different power plants, renewable energy sources, transformers, transmission lines and distributed grids that need to work together properly in considerations of reliability, stability and efficiency [3]. However, the power system dynamic nature driven by changeable demand, and severe environmental regulations, pose important challenges for grid operators. Among such challenges, the unit commitment (UC) is a key optimization problem, which is to find the best schedule of power generating units to meet the demand during a certain period, subject to some constraints of operation, such as minimum time of uptime/downtime, ramp rate of the power generating units, and cost of fuel consumption. Solving for efficient UC is essential in ensuring grid reliability, operational cost minimization and emission reduction [4,5].

The need for optimization in power systems cannot be overstated. Energy markets increase in size and penetration of renewable energy, such as distributed generator (DG) [6-8]. Accordingly, conventional heuristic methods for UC are becoming inadequate. Operators are faced with conflicting goals to balance such as minimizing fuel and start-up costs, and maximizing quick response to demand fluctuations. Unoptimized schedules may cause economic losses, inefficiencies of operation, or even blackouts [9]. Optimization methods offer a rational approach to handling these challenges through a systematic mathematical modeling of constraints and objectives to facilitate data-driven decision-making. Advances in computational power and algorithmic design have further increased the importance of optimization in the modern power system, enabling the solution of large scale, non-linear, and stochastic problems which were once recalcitrant [10].

In the last few decades, a lot of different optimization methods have been used to solve problems regarding power systems operation. Dynamic Programming (DP) is an early solution technique that decomposes UC into sub problems. However, it suffers from the exponential growth of its computational effort with system size. Thus, it is primarily feasible for very small systems as demonstrated by Hou's team [11]. Pure Integer Programming (IP) formulations for UC accurately manage on/off decisions. However, it has rapidly become unmanageable as system size and constraint complexity increase, rendering them impractical without decomposition or simplification. Montero's research team states that IP models have trouble functioning with large UC systems unless they are used with heuristics or approximation methods [12]. Lagrangian Relaxation (LR) has also been applied as a decomposition method, relaxing coupling constraints to divide UC into sub problems. Large systems can be handled by LR technique in theoretical terms, but its implementation is difficult, and solution convergence could be slow [13]. Stochastic Programming (SP) provides reliable UC solutions, but there is frequently a large computational overhead. Valencia Diaz's team noted that growing system size will severely increase solving times and scenarios management complexity [14]. Mixed-Integer Linear Programming (MILP) formulations continue to be the most widely used approach. Yet, according to the O'Malley team, its computational demands fail to scale well with system size, particularly when modeling complex network constraints, and frequently call for heuristic improvements or relaxations to achieve feasible runtimes [15].

Several studies have resorted to swarm intelligence and evolutionary algorithms for UC in order to overcome the challenges of conventional approaches [16]. Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), for instance, have been extensively used in UC and economic dispatch, often yielding high-quality results [11,17]. GA renders can manage the nonlinear constraints and discrete on/off decisions. However, as Yang's team showed, it frequently suffers from high computational cost in large-scale systems or when dealing with high-dimensional constraints [15]. PSO's ability to manage multiple constraints and nonlinear, discontinuous cost functions without requiring gradient information has allowed it to be proven effective for UC. Because of its robustness and simplicity, PSO can be utilized for power scheduling. Nevertheless, according to Li's team, it does not preserve solution quality as complexity and dimensionality increase [18]. An additional popular option is Ant Colony Optimization (ACO), where generator schedules are constructed by probabilistic ants. However, according to Nassef's research team, modifications with different algorithms are necessary in complex UC tasks with discrete constraints in order demonstrate its efficacy. [19]. Likewise, nature inspired heuristics such as the Firefly Algorithm (FA), a nature-inspired technique where fireflies move according to attractiveness that is proportional to their brightness, has been applied to UC [20]. UC solutions have also been investigated via the Artificial Bee Colony (ABC) method when dealing with multi-modal sites. Although the ABC algorithm is simple to solve, it usually necessitates numerous function evaluations or hybridization with other heuristics, as stated by Alshammari's team, to achieve consistent performance across a variety of problem instances [21]. Newer algorithms, such as Harmony Search (HS), and Teaching Learning Based Optimization (TLBO), have been shown to be flexible and adaptable to complex UC objectives. However, settings like pitch adjusting rate and harmony memory size have a significant impact on HS performance. Wang's team looked into how improper tuning can lead to slow convergence and suboptimal outcomes [22]. Whereas, TLBO may show slow convergence when dealing with highly constrained or multi-objective scheduling problems as Diaz's team found [23]. There are Many other approaches that have been employed to deal with the unit commitment problems, like Evolutionary Programming (EP) [24], Ant Lion Optimizer (ALO) [25], Artificial Fish Swarm Algorithm (AFSA) [26], Artificial Sheep Algorithm (ASA) [27], Gravitational Search Algorithm (GSA) [28], Imperialist Competitive Algorithm (ICA) [29], Sine-Cosine Algorithm (SCA) [30], Whale Optimization Algorithm (WOA) [31].

In general, bio-inspired heuristics like PSO and FA are frequently hybridized to the UC problem to improve solution convergence and quality. For example, A Modified Firefly Algorithm (M-FA) has been proposed as a suitable method for scheduling of power system operation to improve UC scheduling. Hussein's research team applied the M-FA to a 10-unit commitment problem. The team first used a priority list heuristic to select committed units, and then tuned generation levels with M FA. The results showed that the M-FA outperformed both the classical firefly algorithm and a standard PSO in matching generation with load and minimizing cost [32]. Similarly, the Rastgou and Bahramara team found that the Adaptive Modified Firefly Algorithm (AMFA) solved the UC problem more effectively than other metaheuristic approaches when applied to multiple test systems, up to 38 generators and IEEE 118 bus [33]. Adaptive memory structures are used by Tabu Search (TS) to avoid revisiting previous solutions, thereby avoiding local optima in the UC combinatorial space. When combined with hybrid approaches, like the PSO-TS scheme, it appears to be more cost effective and robust than standalone metaheuristics [34]. Additionally, Simulated Annealing (SA) has been adapted for UC. combining SA and TS improves convergence stability and lowers UC costs compared to using either traditional SA or TS alone [35]. In order to balance exploration and exploitation, more complex hybrids, such as GA–PSO hybrids or PSO–Grey Wolf hybrids, combine several algorithms. Superior UC solutions are developed by the GA–PSO hybrid, which combines rapid local convergence of PSO with the global search capabilities of genetic algorithms. Compared to standalone GA or PSO implementations, this synergistic approach usually results in faster convergence and higher schedule quality [36]. Blending PSO and Grey Wolf Optimizer (GWO) algorithms to create a balanced search algorithm suited to UC challenges. When compared to standard PSO and GWO methods alone, recent convergence studies in transmission scheduling show enhanced global search capability and stability [37].

Although many different algorithms have been created to address UC problems, both classical and metaheuristic approaches possess a number of common drawbacks. Scalability is still a big issue, especially as power system get more complicated [38]. When applied to large-scale systems or high-resolution time frames, the majority of optimization

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techniques face increased computational difficulties, frequently necessitating simplifications that compromise accuracy. Furthermore, a lot of algorithms struggle to adequately model the uncertain and stochastic aspects of real-world operations, like fluctuating demand [17]. They also frequently need a lot of parameters tuning, have no theoretical assurances of optimality, and can converge prematurely to suboptimal solutions [12,39]. Advanced and hybrid versions enhance the performance at the cost of more complex algorithms, which makes validation and implementation more difficult. These drawbacks show how more robust, adaptable, and computationally efficient algorithms are required to meet the changing demands of modern power system [15,30,40].

Garra Rufa-inspired optimization (GRO) has recently been proposed by Jaber's team, and it showed remarkable success in solving different high complex optimization engineering problems [41-44]. GRO is a novel metaheuristic influenced by the foraging behaviors of Garra Rufa fish. In this paper, GRO is selected to solve the UC problem for 10 units, with a 24-hour supply demand. Furthermore, GRO results are compared with three other algorithms, which are GWO, SWO and PSO, results regarding generation cost and generation-demand matching error.

2. GRO ALGORITHM

GRO algorithm draws inspiration from the way Garra Rufa fish behave during spa therapy sessions or group feedings. The fundamental concept is to divide the swarm of potential solutions into several groups, each with a leader and several followers. To investigate promising regions, some followers may transition from weaker to stronger leaders between iterations, providing flexibility in finding the optimal point in the method [45]. Each group leader in GRO represents the best local solution, and through these leader/follower crossovers, groups can share information. By permitting followers to migrate between groups and occasionally reassigning the most capable leader to lead the largest group, GRO maintains diversity. GRO can investigate several regions of attraction in the solution space thanks to its adaptable structure, which lowers the possibility of premature convergence. GRO process has three main stages - GRO initialization, Crossover of leaders, and followers.

With regard to the initialization, at the heart of the GRO methodology consists the idea of partitioning the entire particle population into several subgroups. Every subgroup is informed by different global and local optimal reference points. The algorithm works on some basic premises. For example, the notion that every particle can act as a leader or follower, depending on the location of the best position for the particle's group as a whole. During each iteration, some of the followers might abandon ineffective leaders, to join more successful ones which produce better optimal values. Before this transition is made, some maximum allowable percentage of such follower shifts have to be established. This frame work provides the background for the process of initialization, which is expressed in Eq. (1) [46]

$$fish\_followers\ no = \frac{partcles\ no - group\ no}{groups\ no} \tag{1}$$

For leaders' crossover, the GRO method is based on two different stages of the leader crossover and this plays an essential role in its run. Initially, each group finds a new candidate to assume the leadership role. Following that, another more selective process occurs in which the most able leader is chosen who can attract and lead the largest percentage of followers. These steps are not mere process but out of the basis of what makes the approach adaptable, that this technique is dynamic and responsive.

Finally, for followers' crossover stage, due to the adaptable movement across groups, there is a high probability of locating the optimal solution within the search domain. GRO utilizes an ample exploration tactic by enabling crossover among group followers. This involves random choosing of members from each group to follow a more dominant leader. Following that, an update step is performed toward the leaders by calculating both the velocity (v_i) and the position (X_i) according to the conventional standard forms given in *eq. (2)* and *(3)*.

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i(t) - X_i(t)) + c_2 r_2 (G_i(t) - X_i(t)) \tag{2}$$

$$X_i(t+1) = X_i(t) + v_i(t+1) \tag{3}$$

where c1, c2 are the acceleration constants and ω is the inertia weight.

The fitness values for each group are updated by incorporating both leaders and followers into the evaluation process. The revised steps of the GRO method are outlined in *eq. (4)* and *(5)*, where £ is the percentage of moving fish between leaders, and r_1, r_2, r_3 are random numbers.

$$trans\ fish\_followers_i = int\ (\pounds * r_3) \tag{4}$$

$$fish\_followers_{ij} = Max\ ((fish\_followers_{ij-1} - trans\ fish\_followers_i), 0) \tag{5}$$

3. COST OBJECTIVE FUNCTION

Electricity must be reliably supplied at all times across all regions of a power system. In addition to minimizing the total generation cost, unit commitment problems also aim to satisfy load demand, ensure adequate spinning reserve, and comply with various operational constraints [38]. To address these objectives effectively, the scheduling time horizon can be determined as follows [47].

$$cost_{nh} = \sum_{k=1}^{n} \sum_{i=1}^{h} \left[FC_i(P_{ih}) + STC_i\left(1 - U_{i(h-1)}\right)\right] U_{ih} \tag{6}$$

where h represents the hours, n = the total units' number, $FC_i(P_{ih})$ is the fuel cost of i^{th} unit with power output (P_{ih}) at its corresponding hour, which is estimated as:

$$FC_i(P_{ih}) = a_i + b_i P_{ih} + c_i P_{ih}^2 \tag{7}$$

STC_i represents start-up cost of its corresponding unit. U_{ih}= ON/OFF status of the i^{th} unit at its corresponding hour, '1' represents ON while '0' represents OFF.

$$STC_i = \begin{pmatrix} Csc_i \; when \; X_i^{off} > MD_i + C_s \\ Hsc_i \; when \; X_i^{off} \leq MD_i + C_s \end{pmatrix} \quad (8)$$

where Csc_i represents the cold start-up cost, MD_i represents the minimum down-time, C_s represents cold start-up hours, and Hsc_i represents hot start-up cost.

The constraints of UCP are considered as three terms which are power equality, spinning reserve, and generation limit which are show in *eq. (9)-(11)*, respectively.

$$\sum_{i=1}^{n} P_{ih} U_{ih} = D_h \quad (9)$$

$$\sum_{i=1}^{n} P_{i(max)} U_{ih} \geq D_h + R_h \quad (10)$$

$$P_{i(min)} \leq P_{ih} \leq P_{i(max)} \quad (11)$$

where D_h represents the load demand per hour, $P_{i(min)}$ = minimum unit generation, $P_{i(max)}$ = maximum unit generation.

To find the minimum cost, a derivative of *eq. (7)* to the unit generation power is calculated as follows:

$$\frac{\partial FC_i(P_{ih})}{\partial P_{ih}} = \lambda_{ph} = 2\alpha_i P_{ih} + \beta_i \quad (12)$$

$$P_{ih} = \frac{\lambda_{ph} - \beta_i}{2\alpha_i} \quad (13)$$

where λ_{ph} represents the incremental fuel cost of the corresponding hour. The initial values are calculated using *eq. (14)* for each iteration, until reaching the optimal value.

$$\lambda_{\text{ph}} = \text{unifrnd}\left(\lambda_{i(max)}\ , \lambda_{i(min)}\right) \quad (14)$$

$\lambda_{\text{i(max)}}$ and $\lambda_{i(min)}$ are the maximum and minimum incremental fuel cost. The second important condition that must be met is the accepted error value of each suggested incremental fuel cost.

$$error = \sum_{i=1}^{n} \lambda_{\text{ph}} P_{ih} - D_h \quad (15)$$

4. APPLIED ALGORITHMS PROCEDURE

An essential requirement of all algorithms is having initial UC solutions. Accordingly, a Priority List (PL) is taken as an initial solution for the UC problem without respecting the ramp rate constraints. In this first step, the main goal is to assure that the total capacity on the committed units will be able to satisfy the power demand, including total losses and reserved energy.

PL provides a simple and quick method than the traditional unit commitment techniques, as the schedules generate the units in ascending order of their average production cost. The PL vector is the on/off status of each generating unit, and is calculated using the *eq. (16)* [48].

$$priority\ list\ vector = \frac{P_{(max),\text{vec}}}{max.\left[P_{(max),\text{vec}}\right]} + \frac{MD_{vec}}{max.[MD_{vec}]} \quad (16)$$

Furthermore, optimization algorithms are employed to determine the most cost-effective power dispatch for each generating unit. Their primary goal is to allocate generation in a way that meets system demand while minimizing overall operating costs, considering technical constraints such as generation limits and reserve requirements. *Figure 1* represents the flowchart of the proposed algorithm related to UC problem.

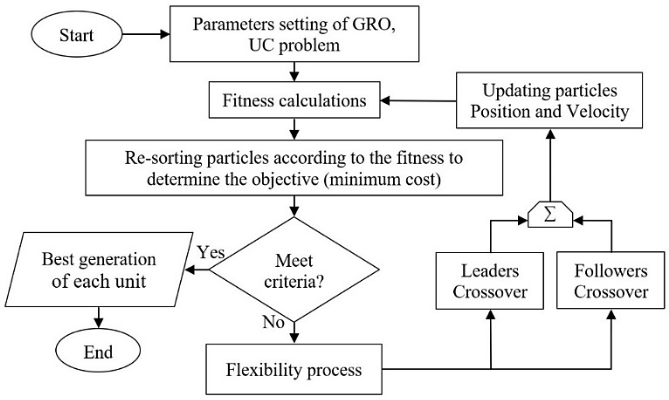

Figure 1. Proposed method algorithm.

As stated, in this work, 10 units with a one-day hourly supply demand is considered. The unit specifications and hourly demand are found in Hussein and Jaber work [32]. GRO method has been implemented to obtain the results. Moreover, GRO results are compared with Gray Wolf (GWO), Spider Wasp (SWO), Particle Swarm (PSO) optimization algorithms. The GWO, SWO, PSO, techniques equations with their parameters' values are implemented without any changes from [49], [50], [51], respectively.

5. RESULTS AND DISCUSSION

This study compares four different optimization methods to assess how a GRO gives better results, with a particular focus on the second step of unit commitment. A 10-unit power system was simulated in MATLAB for this purpose. Several factors were examined in the comparison, including the error between the actual data and the calculated total generated power. For all methods, the selected units that meet the demand are determined using the classical PL method during the ON/OFF decision process. *Table 1* presents the first-step solution to the unit commitment problem. Consequently, the hourly start-up cost can be evaluated as a function of the number and type of generators, as presented in *table 2*.

The estimated generation cost values vary across the optimization methods and time intervals. A noticeable discrepancy is observed among the methods in terms of their relative performance at different hours, which can be attributed to variations in the number of generators considered. The number of generators, in turn, influences the computational complexity of the corresponding cost

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estimations and the errors. *Figure 2* illustrates the total generation cost of the optimization methods during operation hours, while *table 3* shows the total cost in one day.

Table 1. ON (O) / OFF (F) status matrix for the 10 units

HOUR	Unit no									
	1	2	3	4	5	6	7	8	9	10
1	O	O	F	F	F	F	F	F	F	F
2	O	O	F	F	F	F	F	F	F	F
3	O	O	F	F	F	F	F	F	F	F
4	O	O	F	F	O	F	F	F	F	F
5	O	O	F	F	O	F	F	F	F	F
6	O	O	F	O	O	F	F	F	F	F
7	O	O	O	O	O	F	F	F	F	F
8	O	O	O	O	O	F	F	F	F	F
9	O	O	O	O	O	O	F	F	F	F
10	O	O	O	O	O	O	O	F	F	F
11	O	O	O	O	O	O	O	O	F	F
12	O	O	O	O	O	O	O	O	O	F
13	O	O	O	O	O	O	O	F	F	F
14	O	O	O	O	O	O	F	F	F	F
15	O	O	O	O	O	F	F	F	F	F
16	O	O	O	O	O	F	F	F	F	F
17	O	O	O	O	O	F	F	F	F	F
18	O	O	O	O	O	F	F	F	F	F
19	O	O	O	O	O	F	F	F	F	F
20	O	O	O	O	O	O	O	F	F	F
21	O	O	O	O	O	O	O	F	F	F
22	O	O	F	F	O	O	O	F	F	F
23	O	O	F	F	F	O	F	F	F	F
24	O	O	F	F	F	F	F	F	F	F

Table 2. Starting-up cost for the day hours

Time (h)	Start-up cost ($)	Time (h)	Start-up cost ($)
1	0.00	13	0.00
2	0.00	14	0.00
3	0.00	15	0.00
4	900.00	16	0.00
5	0.00	17	0.00
6	1120.00	18	0.00
7	1100.00	19	0.00
8	0.00	20	690.00
9	340.00	21	0.00
10	520.00	22	0.00
11	60.00	23	0.00
12	60.00	24	0.00

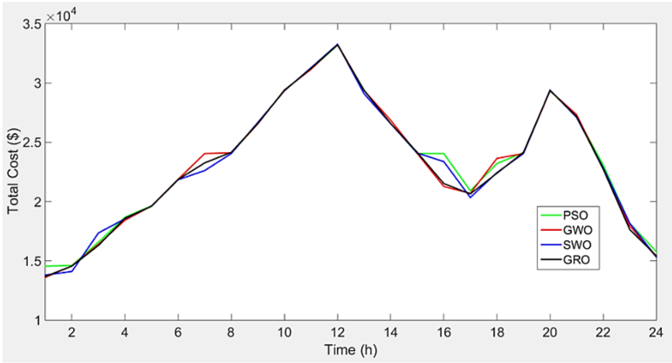

Figure 2. The total generation cost of the optimization methods

Table 3. Total cost for all methods

Method	Total Fuel cost ($)	Total Start-up cost ($)
PSO	560303	4790
GWO	555681	4790
SWO	555302	4790
GRO	553570	4790

It can clearly be noticed that total start-up cost of all methods is the same depending on the PL method results before the optimization. The results show that when applying the proposed GRO method, the total cost is reduced compared to conventional approaches. The total cost of each method is 565093, 560471, 560092, and 558360 for PSO, GWO, SWO, and GRO, respectively. This reduction is achieved because the proposed method is more efficient in considering the optimal generation of each unit and for each hour. *Figure 3* illustrates the differences in the daily error among the algorithms.

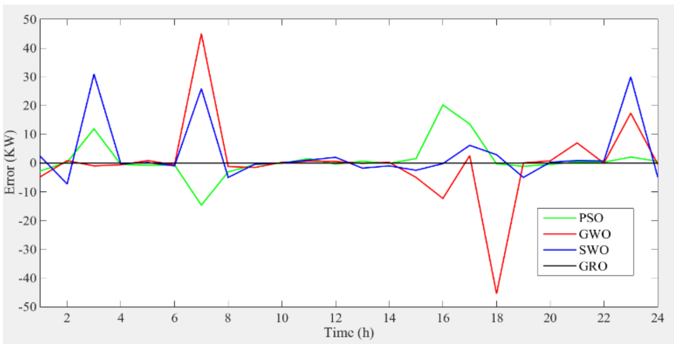

Figure 3. The daily error for the algorithms

Figure 3 shows the superiority of the proposed method over the other methods, despite the fact that all methods yield acceptable error percentages. In contrast, other optimization techniques that lack such mobility often struggle when navigating such as across complex landscapes, particularly when dealing with systems governed by numerous variables or high-order differential equations.

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For example, maximum error percentage is 0.00357% at t = 8 h while the max error value is -45.4766 kW at *t* = 18h and both of the cases are obtained by GWO. *Figure 4* presents the objective function convergence values recorded during 15 iterations for randomly selected hours, which are 3, 8, 15, and 22.

The time for each method was calculated for 50 runs using Dell core i7 and the results for the GWO, SWO, PSO, and GRO as: 0.0811, 0.118, 0.0783, and 0.0793 second, respectively. Although all methods can be considered fast, GRO is considered the second fastest, with a slight difference from method of PSO. Despite this difference, it is considered practically acceptable due to the noticeable improvement in the accuracy of the results.

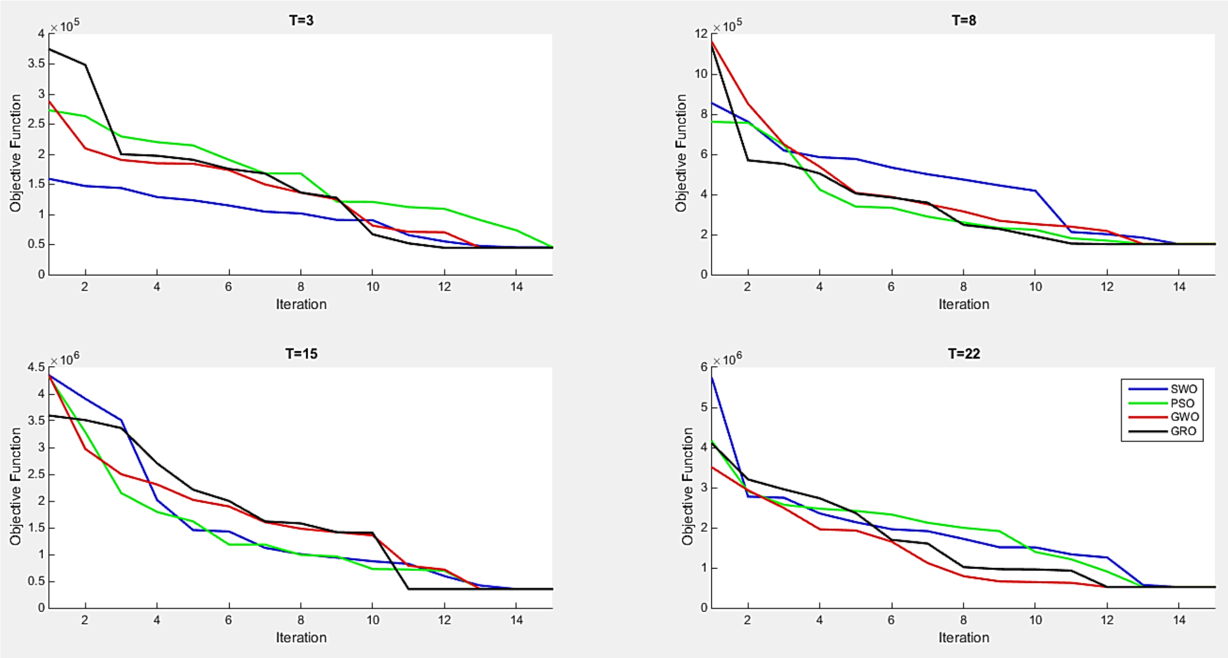

Figure 4. Convergence of objective function

6. CONCLUSION

The unit commitment problem is one of the most important optimization problems in modern power system. Traditional approaches, while basic, often have certain limitations such as being unable to scale up, inefficient computation, and not being able to model stochastic system behavior. To overcome such challenges, this study examines the Garra Rufa inspired optimization algorithm as a new algorithm to solve unit commitment problem. GRO provides a promising way to balance between exploration and exploitation to improve the capability of searching in complex and multi-dimensional solution spaces.

The simulation results revealed that the proposed methos has the lowest total generation cost of $558,360 which is better than the values of PSO ($565,039), GWO ($560,471) and SWO ($ 560,092) by significant margins. Furthermore, although all the methods meet standard error limits, GRO consistently provides less scheduling error, which is indicative of more precise unit commitment dictions, and improved operational reliability. To sum up, the simulation results clearly proved the superiority of GRO in cost minimization and accuracy improvement. For future work, the application of GRO will be further explored in larger and real world grid environment to evaluate its performance and explore its integration with hybrid frameworks to unleash its full potential in smart grid applications.

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Aws Al-Taie: Formal analysis, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Aqeel S. Jaber: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing - review & editing.

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