Solving Dynamic Combined Economic Environemental Dispatch Problem with Renewable Energies and Constraints Using Gorilla Troops Optimizer

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ABSTRACT

The primary goal is to optimize the hourly allocation of power generation outputs by minimizing operational costs, pollutant emissions, and transmission losses, and ensuring compliance with a range of equality and inequality constraints. To tackle this challenge, a novel metaheuristic algorithm inspired by gorilla's behavior is proposed. Gorilla Troops Optimizer (GTO) was applied to 5- and 10-generator unit systems, integrating variable wind and solar energies over a day with varying load demands. To demonstrate the effectiveness of the GTO algorithm in handling the hybrid dynamic combined economic and environmental dispatch problem, including equality constraints, transmission losses, valve-point effects, prohibited operating zones, ramp rates, and power limits, its performance was compared with other optimization techniques. The findings indicate that GTO provides the optimal scheduling of power generators, leading to significant reductions in daily operational costs and emissions with high percentages. Moreover, the integration of renewable energy significantly reduces pollutant gas emissions, fuel costs, and transmission losses, while meeting all imposed constraints. This research positively contributes to enhancing the reliability of power supply systems, while simultaneously reducing environmental pollution, transmission losses, and fuel costs.

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1. INTRODUCTION

The consumption of electrical energy has accelerated in recent decades due to the growth of population and industries. This has led to an increase in the number, length, and complexity of electrical networks, resulting in the depletion of fossil fuels and an increase in Greenhouse Emission Gases that cause climate change. The main challenge in the electric industry is focused on the integration of new production methods, prioritizing renewable energies. This leads to the inevitable trend of developing a low-carbon economy. Renewable energy sources have emerged as a solution to problems such as high operating costs, environmental pollution, electric power shortages, and the long-distance transmission of generated power [1],[2].

Combined Economic Environmental Dispatch (CEED), optimally schedules and allocates the generated power among the power-generating units to meet the predicted load demand over a certain number of time intervals [3], satisfying all equality and inequality constraints, and simultaneously minimizing two objectives operational costs and emissions. Dynamic Combined Economic Environmental Dispatch (DCEED) is an enhanced version of the static one CEED, aiming to schedule power on an hourly basis for a specific day, considering load demand variations [4]. DCEED presents an urgent problem in power system operation optimization. Its task is to adjust the output power of generator units according to the predicted load demand during the dispatch period [5]. According to [4], DCEED is time-dependent, and recognized as an intractable dynamic optimization problem, due to its large dimensionality, multiple local optima, high non-linearity, non-differentiability, non-convexity, competing objectives, and strong constraints. Traditional numerical optimization methods are heavily reliant on problem gradients and are therefore unable to deal with the DCEED problem with the characteristic of non-differentiability. Although these methods can employ approximations to achieve the solvability of DCEED, their computation accuracies cannot be guaranteed. Their high sensitivity to the initial guesses of the solutions will exert a significant influence on the quality of the final solutions, which is harmful to their stabilities in solving DCEED [4]. Moreover, because of the complexity and the large size of the DCEED problem, conventional methods require extensive time to converge, resulting an exorbitant cost. Therefore, researchers have developed new optimization techniques known as ‘‘metaheuristics’’. The word heuristic means the art of descovering new strategies to solve problems. The suffix meta means “upper level methodology Metaheuristics are approximate optimization techniques, they received more and more popularity in the past 20 years. They provide better solutions and overcome the demerits of conventional methods. They are among the most promising and successful techniques. Metaheuristics provide global optimal solutions in a reasonable time for solving hard, large and complex problems in science and engineering. Many metaheuristics are inspired by animal behaviour, in this paper a recently developed metaheuristic optimization algorithm Gorilla Troops Optimizer (GTO) used for finding global optimal [6].

Researchers have worked on the development of different metaheuristic techniques to solve dynamic combined economic dispatch problem. In the literature, different metaheuristics have optimized the DCEED problem. Author in [7] solved the DCEED problem for unit systems with 5 and 10 generators taking into consideration the valve point effects only, using three population-based algorithms which are, Seagull Optimization Algorithm (SOA), Crow search algorithm (CSA), and Tunicate Swarm Algorithm (TSA). The same problem was solved in [8] using Crow Search Algorithm (CSA) and considering ramp rate. In [5] dynamic economic emission dispatch problems of 5 ,10 and 15 generators was solved using an Improved Tunicate Swarm Algorithm (TSA) considering only valve point effects. Other studies have tackled the dynamic multi-objective problem of economic and environmental dispatch by incorporating the uncertainty of renewable energies. For instance, [2] and [9] modeled the uncertainty of wind energy using the Weibull distribution. They employed the Improved Sailfish Algorithm (ISA) and the Hybrid Flower Pollination Algorithm (HFPA) respectively. Many other studies have opted for the hybridization of two metaheuristics to solve the problem of environmental and dynamic dispatching [10] applied two metaheuristiques based on particle swarm optimization (PSO) and termite colony optimization (TCO) for solving Dynamic economic dispatch problem on 5, 10 and 30 generators taking into consideration ramp rate and valve point effect. Currently, the trend in solving the DCEED problem involves integrating renewable energie sources (RES) such as solar and wind energies alongside conventional production methods. Electricity will be produced from hybrid sources; the problem will be addressed as Hybrid Dynamic Combined Economic Environemental Dispatch (HDCEED). The mentioned studies show that a few have optimized the HDCEED problem by considering the several constraints such as valve effects, ramp-rate effects, and the impact of prohibited operating zones.

In the present paper, authors applied a recent metaheuristic which mimics the behavior of gorillas for solving HDCEED problem with radiation and wind variations throughout the day, considering different constraints and limits including equality constraint, lower and upper bound generator limits, ramp rate limits, valve effects, and prohibited zone constraints. On the other hand, authors aim to minimize transmission losses.

The contribution of this article can be summarized as follows:

Application of a new metaheuristic gorilla troops optimizer to solve a bi-objective DCEED problems with different constraints, valve effects, ramp rate and prohibited zone limits. Transmission losses are taken into consideration.

Solving the DCEED problem with the integration of variable solar and wind energy throughout a day.

Proving the efficiency and robustness of GTO for solving the DCEED problem by comparing it to other metaheuristics.

The ¨performance of the GTO algorithm is validated and proved by applying it on 5 and 10 unit systems.

2. FORMULATION OF THE PROBLEM

The goal of integrating renewable energy sources into the DCEED with valve effects, ramp rate, and prohibited zone limits system is to minimize two factors simultaneously for hourly load demand, which are overall expenses and emissions linked to thermal power plants by enhancing their operating efficiency. The equality and inequality constraints must be satisfied. The primary difficulty with such an optimization problem is associated with the presence of conflicts between two features, for which we have converted this problem into a single-objective optimization by introducing a wighting factor. The objective function is expressed as follows [4], [11]:

$$F=\omega(F_T)+Pp_f(1-\omega)\,E_m \quad (1)$$

Where F is the objective function, F_T is the total fuel cost, E_m is the total pollutant emissions, ω represents the weighting factor which converts the two objectives problem into a single objective one, it is set at 0.5. Pp_f is the price penalty factor the following function:

To determine the price penalty factor "Pp_f" associated with a given load, the following steps must be followed:

- Calculate the ratio $\frac{F_{ci}^t(P_{i,max})}{E_i^t(P_{i,max})}$ for each generator;
- Sort the factor values obtained in ascending order;
- Add the maximum generated power of each generator ($P_{i,max}^t$) one by one, starting with the plant capacity with the lowestPrice factor corresponding to the given load. Once $\sum P_{i,max} \geq P_D$ stop calculation, P_D is the power demand;
- At this stage, "Pp_f" connected to the last unit in the summing process is the price penalty factor corresponding to the given load [12].

The total cost F_T is given by (2).

$$F_T=\sum_{t=1}^{T}\left(\sum_{i=1}^{N} F_{ci}^t(P_i^t) + \sum_{j=1}^{Nw} F_{wj}^t(P_{wj}^t) + \sum_{k=1}^{Ns} F_{sk}^t(P_{sk}^t)\right) \quad (2)$$

In reality, the ripple effects induced by modern steam turbines with multi-valve, create nonlinearity and no convexity in the fuel cost function[14].Considering the valve-point effect the fuel cost is computed for the t_{th} interval as :

$$F_c=a_iP_i^2 + b_iP_i + c_i+\left|d_i(\sin\,(e_i(p_i^{min} - p_i^t)\right| \quad (3)$$

where $a_i, b_i, c_, d_i$ are cost coefficients for the i_{th} conventional energy source.

The cost of the j_{ih} wind turbine at t_{th} time can be computed as :

$$F_{wj}^t = d_jP_{wj}^t \quad (4)$$

$$P_{wj}^t \begin{cases} 0 & v_t \leq v_i \; or \; v_t \geq v_o \\ \varphi\,(v_t) & v_i \leq v_t \leq v_r \\ P_{wr} & v_r \leq v_t \leq v_o \end{cases} \quad t = 1,2 \ldots.T \quad (5)$$

$$\varphi\,(v_t) = P_{wr}\frac{v_t-v_i}{v_r-v_i} \quad (6)$$

v_t : Forecast wind speed at hour t;
v_i : Cut in wind turbine speed;
v_r : Cut in wind turbine speed;
v_o : Cut out wind turbine speed;
$\varphi\,(v_t)$: wind power generation;
P_{wr} : Equivalent rated power output for wind power generation;
d_j: Direct wind power cost;

The cost of the k_{ih} solar panel at t_{th} time can be computed as :

$$F_{sk}^t(P_{sk}^t) = S_KP_{sk}^t \quad (7)$$

$$P_s^t(G_t) = \begin{cases} P_{sr}\frac{(G_t)^2}{G_{std}R_c} & 0 < G_t < R_c \\ P_{sr}\frac{G_t}{G_{std}} & G_t > R_c \end{cases} \quad t = 1,2 \ldots.T \quad (8)$$

G_t : Forecast solar radiation at hour t;
G_{std} : Solar radiation in the standard environment set as 1000 W/m^2 ;
R_c : A certain radiation point set as 150 W/m^2 ;
P_{sr} : Equivalent rated power output of the PV generator;

The total emissions of the i_{th} thermal units in one day can be found as :

$$E_M=\sum_{t=1}^{T}\left(\sum_{i=1}^{N} \alpha_i(P_{gi}^t)^2 + \beta_iP_{gi}^t + \gamma_i+\delta_i exp\,(\Theta_ip_i^t)\right) \quad (9)$$

Where $\alpha, \beta_i, \gamma, \delta_i$ and Θ_i. are pollutant discharge coefficients.

2.1. Power balance (Equality constraints)

The total power generated must be equal to total power demand along with transmission losses as at time t described as follows.

$$\sum_{i=1}^{N} P_i^t + \sum_{j=1}^{Nw} P_{wj}^t + \sum_{k=1}^{Ns} P_{sk}^t = P_D^t + P_L^t \quad (10)$$

P_D^t = Active power demand at hour t (MW)
$P_{L_l}^t$ = Hourly active transmission losses (MW)
The exact value of the transmission losses can only be obtained from a study of the power flow. Nevertheless, in studies of the economic dispatching, transmission losses are often expressed as a function of the active powers generated. This technique is commonly referred to as the B coefficient method. In this approach, the losses are approximated by the Kron formula as below [13], [14], where the terms are called coefficients of losses

$$P_l^t = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i^t B_{ij} P_j^t \quad (11)$$

Where the terms B_{ij} are called coefficients of losses

2.2. Generating capacity constraints (inequality constraints)

The active power generation output of each thermal generator must remain within specific minimum and maximum bounds. The limitations and restrictions imposed on the operation of power production units over a period of time are power generation constraints. These constraints are crucial for ensuring the secure and reliable operation of the power system. The functional expression of output power constraints of solar, thermal and wind turbines is shown as equation (12). Where $P_{i,min}$, $P_{i,max}$ are the upper and lower limits of the output power of thermal power units P_{wr} and P_{sr} are the rated output power of wind turbine and solar panels respectively .

$$\begin{cases} P_{i,min} \le P_i^t \le P_{i,max} \\ P_s^t \le P_{sr} \\ P_w^t \le P_{wr} \end{cases} \quad (12)$$

The ramp rate limits of thermal generators are essential parameters in power system operation and control. The ramp rate denotes the maximum rate at which a generator's power output can change within a specified time frame. Sudden and significant fluctuations in power output from generators may result in grid instability. Therefore, by enforcing ramp rate limits, system operators ensure that changes in power output occur gradually, thus aiding in maintaining grid stability. Slope constraint expression of thermal power unit is as in (13). Where $P_{URi}$and P_{DRi} are the upper and lower limits of the slope of the thermal power unit.

$$\begin{cases} P_i^t \le P_i^{t-1} + P_{URi}\,, & P_i^t > P_i^{t-1} \\ P_i^t \ge P_i^{t-1} - P_{DRi}\,, & P_i^t < P_i^{t-1} \end{cases} \quad (13)$$

Constraints Due to prohibited operational zones are described as follows:

$$P_i^t \begin{cases} P_i^{min} \le P_i^t \le P_i^1 \\ P_i^{-k-1} \le P_i^t \le P_{-i}^k & \text{k=2,……}z_1 \\ P_i^{-z_i} \le P_i^t \le P_i^{max} \end{cases} \quad (14)$$

Where z_i is the number of prohibited operating zones for thei_{th} unit, P_i^{-k} and $P -_i^k$are upper and lower bounds of the prohibited zone number k.

3. RESEARCH METHOD

3.1. Gorilla Troops Optimizer (GTO)

Gorilla Troop Optimization (GTO), introduced by Abdollahzadeh and al. in 2021, is a recent optimization technique. This novel metaheuristic is designed to simulate the social intelligence and life cycle of wild gorillas. Gorillas are sociable animals that live in groups, known as troop, these troops are structured around an adult male, known as the silverback, who assumes the role of leader, making crucial decisions and safeguarding the troop. The remaining members of the troop, including groups of female gorillas and their offspring (referred to as the black backs), follow the leadership of the silverback. Notably, the silverback earns its name from the silver-colored hair that develops on its back during puberty, and it typically has a lifespan exceeding 12 years. Similar to other apes, gorillas have feelings, make and use tools, establish strong family bonds, and think about their past and future. They perform such activities as taking rest, traveling, and eating during the day [15], [16]. In this algorithm, each gorilla in the population represents the potential solution to the optimization problem. The silverback is considered as the best solution, then the gorilla's candidates tend to approach to it and leave the weakest member as it is the worst solution. Moreover, this algorithm is based on the exploration and exploitation phases to simulate the gorilla behaviours [17]. The exploration phase is mainly used to perform a global search of the space it has three main operators summurized mathematically as follows. p is a parameter ranging from 0 to 1 which is utilized to choose one of the three mechanism.

rand < p: Migration to unknown regions of the search space is increasing the exploration.

rand ≥ 0.5: movement of solution (gorilla) to another one balances exploration and exploitation of the search space.

rand < 0.5: The movement toward the known location of the search space enhances the exploration capability different optimization spaces and reinforces the GTO in escaping from local optimal points [15], [18].

$$GX(t+1) = \begin{cases} (UB - LB) \times r_1 + LB & rand < p \\ (r_2 - C) \times X_r(t) + L \times H & rand \geq 0.5 \\ X(i) - L \times (L \times X(t) - GX_r(t) + r_3((X(t) - GX_r(t))) & rand > 0.5 \end{cases} \tag{15}$$

$GX(t+1)$ indicates the candidate position vector of the gorilla at the next iteration, and X(t) is the current position vector of the gorilla. Moreover, r_1, r_2, r_3 and rand are the random values between 0 and 1. UB and LB indicate the upper and lower bounds of the variables, respectively. X_r and GX_r are the candidate position vectors of gorillas that are selected randomly. The equations that are used to calculate operators C, L and H are as follows [20]:

$$C = F \times (1 - \frac{It}{maxIt}) \tag{16}$$

$$F = \cos(2 \times r_4) + 1 \tag{17}$$

$$L = C \times l \tag{18}$$

$$H = Z \times X(t) \tag{19}$$

Z=[-C,C]

C refers to competition for adult females encourages gorillas to challenge each other and compete for the best slutions,enhancing both exploration and exploitation$L$ is used to simulate the silverback leadership, leveraging the guidance of the best solutions found by the leader or leading gorillas, and focusing on exploiting the most promising areas of the search space..H simulates hierarchy establishes a structured movement where dominant gorillas exploit good solutions, while lower-ranked individuals explore new areas, ensuring a balanced search strategy [14].

It and $maxIt$ are the current iteration and the maximum number of iterations in the optimization problem. r_4 is a random value that is between [−1,1]? On the other hand, the exploitation phase has two strategies.

Follow the silverback maintains the systematic and continued exploration in individual groups to ease exploitation.

Competition for adult female, which mimic the group expansion and fight process by puberty gorillas [19].

The transition between the two movements is based on C, as defined in equations bellow and W, which is a predetermined value. If C ≥ W, then the gorillas update their location by following the silverback, as follows:

$$GX(t+1) = L \times M \times (X(t) - X_{silverback}) + X(t) \tag{20}$$

$$M = \left(\left|\frac{1}{N}\sum_{I+1}^{N} GX_i(t)\right|^g\right)^{\frac{1}{g}} \quad ; \quad g = 2^L \tag{21}$$

where Xsilverback denotes the location of the silverback gorilla. If C < W, then the locations of the gorillas are updated based on the competition for adult females, which can be expressed as follows:

$$GX(i) = X_{silverback} - (X_{silverback} \times Q - X(t) \times Q) \times A \tag{22}$$

$$Q = 2 \times r_5 - 1 \tag{23}$$

$$A = \beta \times E \tag{24}$$

$$E = \begin{cases} N_1, & rand \geq 0.5 \\ N_2, & rand < 0.5 \end{cases} \tag{25}$$

Where Q is adopted to simulate the impact force, which is calculated by equation (23). Moreover, r_5 is a random value between 0 and 1. Equation (24) is used to calculate the coefficient vector of the violence degree in conflict. β is the parameter that needs to be given before the optimization operation. E is used to simulate the effect of violence on the solution's dimensions. If rand ≥ 0.5, E will be equal to a random value in the normal distribution and the problem's dimensions. However, if rand < 0.5, E will be equal to a random value in the normal distribution; rand is a random value between 0 and 1 [19].

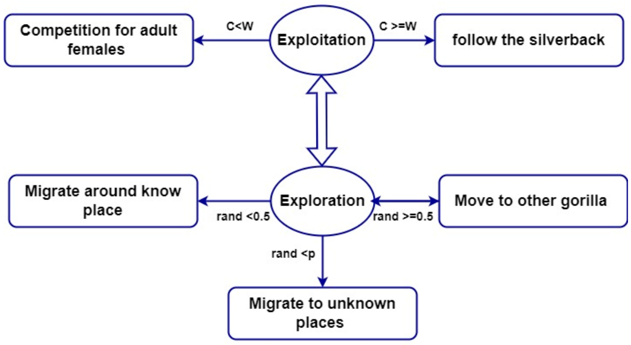

Figure 1. Various phases of exploitation and exploration of GTO [19]

The flowchart of the GTO algorithm applied to the HDCEED problem is structured as Figure 2.

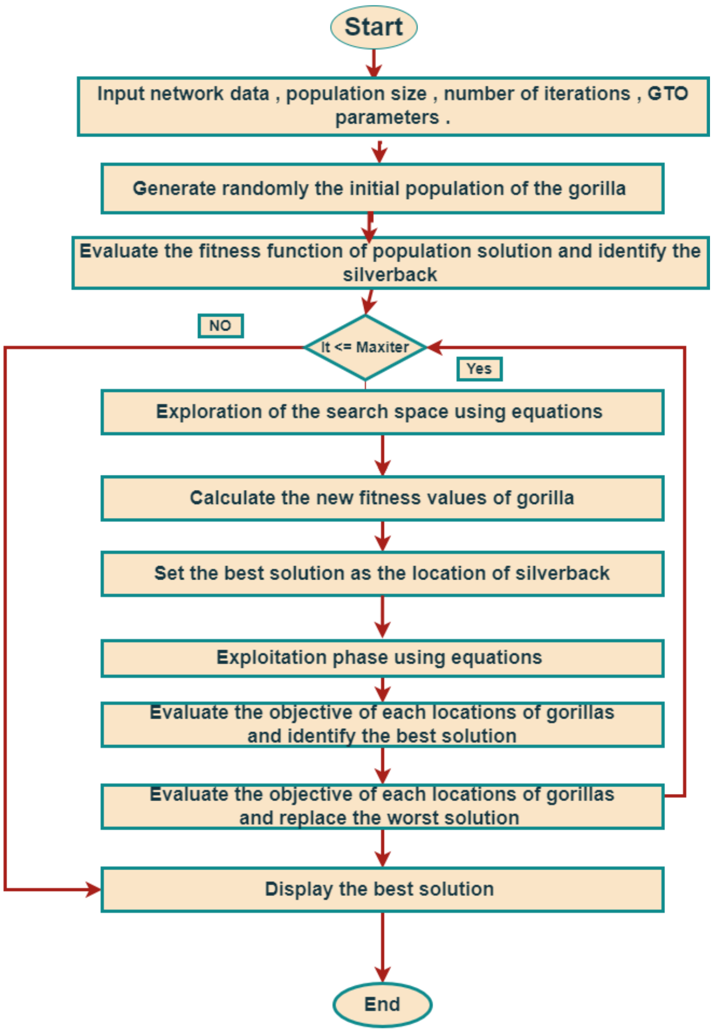

Figure 2. GTO algorithm flowchart

4. RESULTS AND DISCUSSION

In this study, the GTO algorithm is applied to minimize a daily total operation cost and gas emissions in two systems. Test system 1 is composed of 5 thermal power generating units, wind and solar generators. The second system is composed of 10 thermal power-generating units with the integration of solar and wind energy. To make the system more complex and closer to reality, valve effects, ramp rate limits, maximum and minimum generator limits, power balance constraints, and transmission losses are taken into account. prohibited operating zone limits are taken into consideration only on the ten system generator units. The prediction curve of the wind speed and solar radiation is taken from [2] and [20]. Figure 3 presents the wind and solar powers estimated as (5) and (8). The number of iterations was set at 500, the population size was 200 in all the simulations. The simulations were established with MATLAB 2020, it was run on a personal computer with an Intel Core i5 with a processor of 2.4 GHz and a RAM of 8.0 GB under MS Windows 10. Thermal unit data are taken from [7]. The rating of the power generator is 30MW. The cut-in, cut-out, and rated wind speeds are vi=5m/s, vo=45 m/s, and vr=15 m/s respectively. The direct cost coefficient of wind power generators is 1.45. The rating power of solar PV generator is Pr=150 MW. The direct cost coefficient of solar PV generator is taken at 3.5. The solar radiation in the standard environment $Gstd$ and a certain radiation point RC

are taken as 1000 W/m2and 150 W/m2. The daily power demand curve of the two systems is taken from [8].

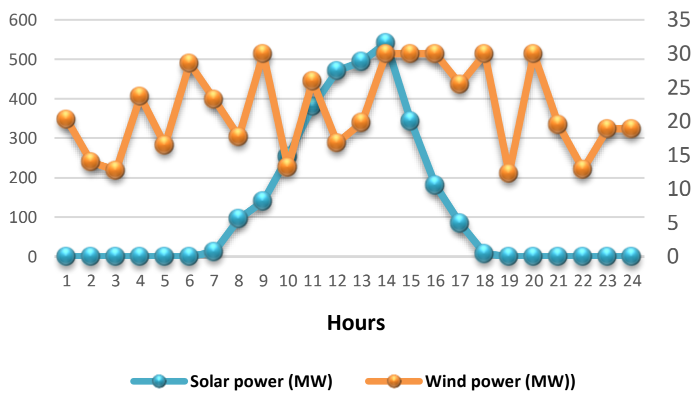

Figure 3. Forecast wind and solar powers for one day.

GTO algorithm's performance in solving HDCEED problem is measured using three performance indicators: operation costs, pollutant emissions, power balance limitations, and constraints. In addition to prove the efficacy and the robustness of the GTO algorithm four cases will be treated and compared with other optimization methods.

Case 1: Solving the DCEED problem with five generating units taking, into consideration valve effects and ramp rate.

Case 2: Solving the HDCEED problem for five generating units with the integration of RES, taking into consideration valve effects and ramp rate.

Case 3: Solving the DCEED problem with ten generating units taking into consideration valve effects, ramp rate limits and prohibited zone limits.

Case 4: Solving the HDCEED problem for ten generating units with the integration of RES, taking into consideration valve effects, ramp rate limits and prohibited zone limits.

4.1. Solving the DCEED problem with five generating units.

To prove the efficiency and robustness of the GTO algorithm. it was rigorously compared with established metaheuristics such as CSA [7], TSA [7], FFA [7] MOALO [20]and PSO [21], MODE [22] The comparative analysis, depicted in Figure 4, highlights the superiority of the GTO algorithm in achieving a reduced total fuel costs in 24 h compared to metaheuristics selected from the literature. Over the entire 24-hour period, the total cost incurred by most metaheuristics was notably higher than that achieved by GTO which was reduced to 32742,8665 USD. Importantly, GTO demonstrated acceptable emission performance in the 5 units' test system when compared to other approaches. Furthermore, Figure 4 shows the GTO Algorithm's exceptional capability in producing optimal daily results for 5 generator units with acceptable transmission loss values.

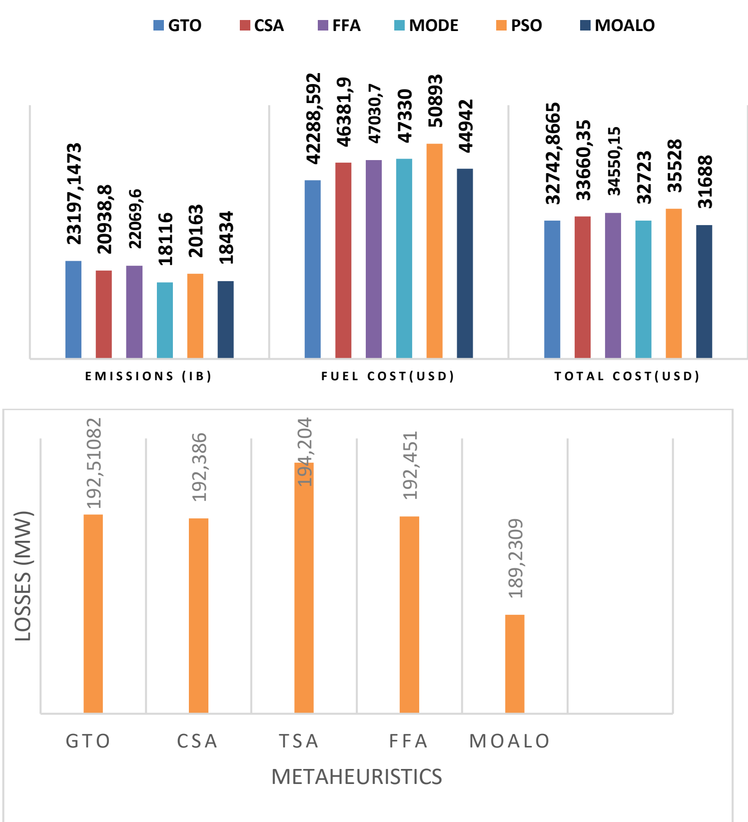

Figure 4. Total fuel cost, total emissions, total cost and losses obtained by GTO and compared with other algorithms on the five-unit test system.

The analysis results for case 1 shows that the GTO algorithm's dispatch scheme was the most effective and respects all constraints especially the equality constraint as shown in the Figure 5.

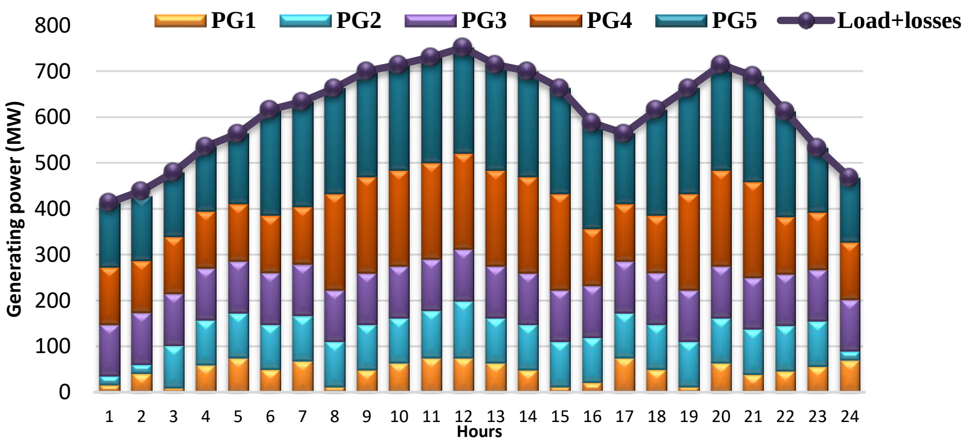

Figure 5. Power balance constraint verification of generator set output power in case 1

4.2. Solving the HDCEED problem with five generating units.

This case shows the important impact of variable solar and wind energies integration in the dynamic economic dispatch problem with valve effect and ramp rates, spatially on the operational cost, emissions and losses. Clearly, the results in Figure 6 indicate the total cost, fuel cost, emissions and transmission losses have significantly decreased when combining solar and wind energy. The total cost decreased by 15.82% when integrating renewable energies. It can be noticed that the gas emissions decreased considerably with a percentage of 49.1278% when wind and PV generators are integrated. In term of daily losses, renewable energies reduce it from 192.39 MW to 117.7671 MW whichis a percentage of 38.78 %. Figure 7 shows that the integration of solar and wind energies simultaneously decreases the amount of electricity produced by thermal power plants, which leads to a reduction in production costs, emissions of polluting gases and transmission losses. that the power generated by the thermal generators fells by 40.89% when wind and solar energy were injected.

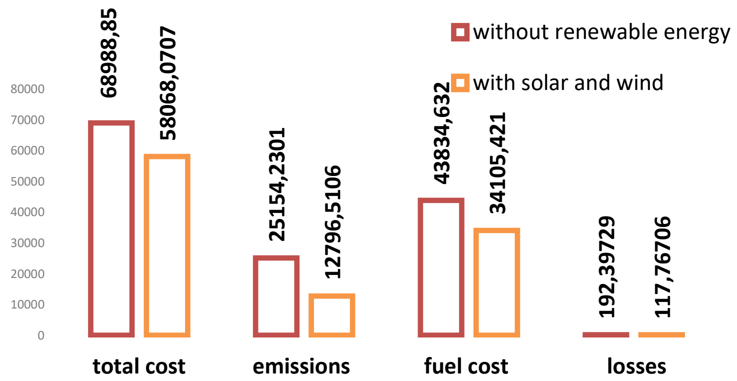

Figure 6. Comparaison of total fuel cost, total emissions, total cost and losses obtained by GTO with and without the integration of renewable energy.

Table 1 shows results obtained by the application of GTO on the HDCEED problem for five generating units at 14 PM. We can notice that at 2 PM the photovoltaic panels and wind turbine are both operational as shown in Figure 1 and deliver the maximum output of the day which explains the flagrant decrease of fuel costs from 2002.57 USD to 642.43 USD, emissions which decrease from 1454.07 Ib to 218.7741 Ib, and transmission losses from 10.0828 to 0.4593 MW in this period. The results indicate that at this period of the day the energy produced by the PV panel is not used in its entirety. The solar generated power was 541.696 MW, only 510.4593 was utilized in order to respect the equality constraints, avoid loss of synchronism and instability of the network frequency. It can be also noticed from Table 2 that in the same period the thermal units were on their minimums, there for we had a minimum cost, emissions and losses compared with the case 1 as shown in the Table 01.

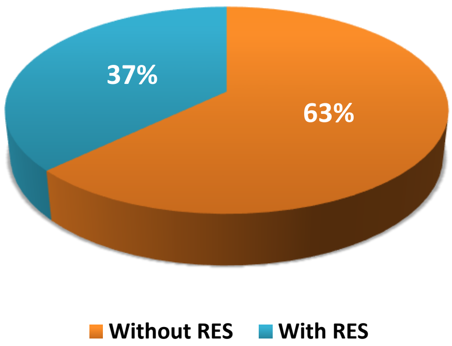

Figure 7. Total power generated by thermal units with and without renewable energy.

Table 1. HDCEED solution in case 2 at 14 O'clock

	With RES	Without RES
Total cost (USD)	2691,3117	3456,636
Fuel cost (USD)	642,43	2002,57
Emissions (Ib)	218,7741	1454,066

Losses(MW)	0.4593	10.0828

Table 2. power generated by the five generators at 2 p.m. with and without RES

Power generators	PG1	PG2	PG3	PG4	PG5
Without RES	45	61,2571	145,2771	250	198.5486
With RES	10	20	30	40	50

4.3. *Solving the DCEED problem with ten generating units*.

In this scenario, we will prove the robustness of GTO by applying it to a larger system of 10 generators. In addition to the valve and ramp rate effects, prohibited zones have been taken into account. the intervals of the prohibited zones are taken from the reference [23]. The results obtained by GTO will be compared with other optimization techniques; CSA [8], MONNDE [24], TLBO [25], CRO [26], IBFA [27], HCRO [26], PSO-CSC [28] as in Figure (8). GTO in figure (8) evidences superior effectiveness in solving complex problems for large networks. Gorilla troops optimizer has a strong ability to reduce operational cost when dealing with DCEED problem for larger networks. Comparison in Figure 8 indicates that the daily fuel and total cost values obtained by GTO were smaller than the other methods of literature. In contrast to the previous cases, emission issue from GTO are much lower in the 10 units' test system comparing to other metaheuristics. The GTO method efficiently minimized total transmission losses to 1294.8502 MW within 24 hours, showcasing a remarkable 31% decrease compared to losses incurred by the CSA method and surpassing the performance of other methods as shown in Figure 9.One of the main objective of this study is to prouve that GTO algorithm can solve the DCEED and HDCEED problems with the statisfaction of all constraints, Prohibited operating zone limits is one of them and it is satisfied for the the generators number 2 , 8 and 10 as it is shown on the table 3. Figure 10 confirms that the sum of the power generated from each unit in each hour is equal to the sum of load demand and transmission losses in the scheduling cycle, which verifies the equality constraint.

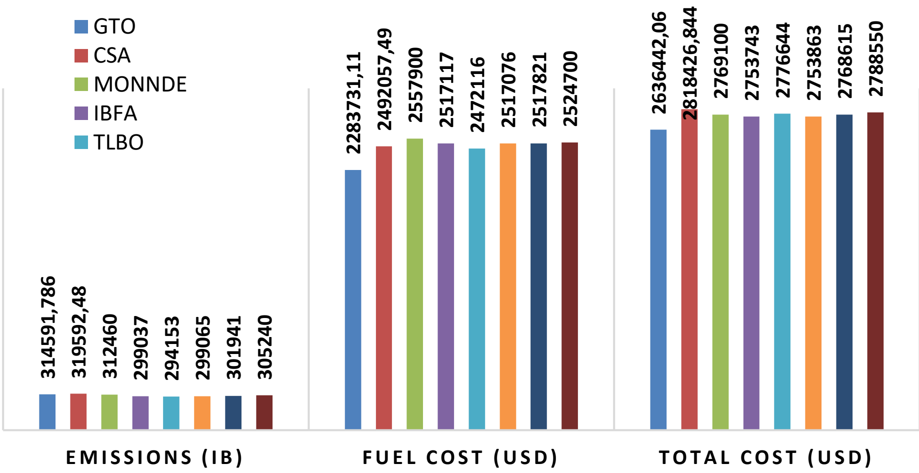

Figure 8. Total fuel cost, total emissions and total cost obtained by GTO and compared with other algorithms for the ten-unit test system.

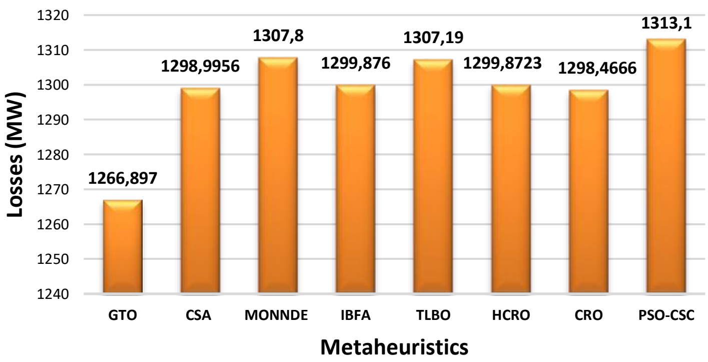

Figure 9. Transmission losses obtained by GTO and compared with other algorithms for the ten-unit test system.

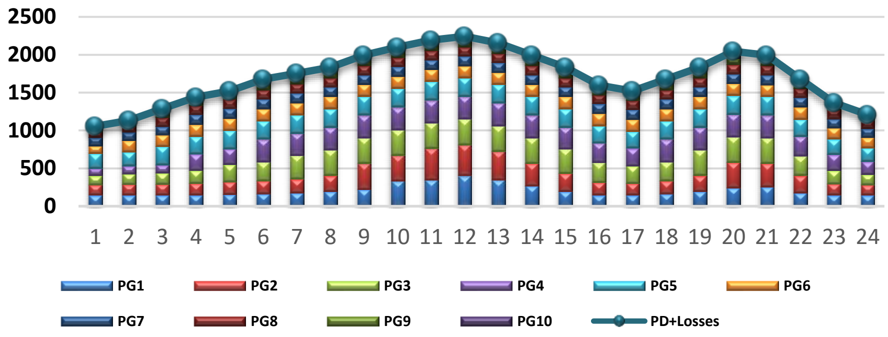

Figure 10. Power balance constraint verification of generator set output power in case 3.

Table 3. power generated by the generators number 2,8 and 10 satisfy the prohibited operating zones

Hours	PG2	PG8	PG10	Hours	PG2	PG8	PG10
01:00	135	71,9993	28,836	13:00	374,4875	120	55
02:00	141,2332	76,09903	31,1454	14:00	294,4875	120	55
03:00	144,1224	117,0951	31,5001	15:00	235,1265	120	55
04:00	157,3442	120	34,442	16:00	169,568	120	47,6063
05:00	166,0976	120	35	17:00	157,1764	120	45,0075
06:00	171,1398	120	55	18:00	170,8709	120	55
07:00	181,8414	120	55	19:00	206,3543	120	55
08:00	206,3542	120	55	20:00	333,0268	120	55
09:00	339,5961	120	55	21:00	308,3023	120	55
10:00	337,1632	120	55	22:00	228,3023	120	46,3338
11:00	413,0539	120	55	23:00	148,3023	113,4204	34,9571
12:00	406,8429	120	55	00:00	135	106,7199	29,0338

4.4. *Solving the HDCEED problem with ten generating units*

In this case, the test system is composed of 10 thermal units with the injection of wind and solar power. Valve effects, ramp rates, prohibited zone limits are taken into consideration, in addition power generator limits, equality constraints and losses are included. It can be seen from the table 5 that the prohibited zone and ramp rates limits are satisfied. Table 4 indicates that the equality constraint is satisfied, i.e. that the power produced by the thermal generators, the photovoltaic panels and the wind turbines have been able to satisfy the power required every hour, it approves the effectiveness of GTO algorithm to maintain the equality constraints with the integration of solar and wind energies. As shown in Figure 11, the injection of photovoltaic panels and wind turbines has reduced emissions and transmission losses with the high pourcentages of 23.28% and 21.59 % respectively. The fuel cost has decreased with a pourcentage of 9.13% in a day. all this meant an 11.28% reduction in total production costs. Figure 12 represents the impact of integration of renwable energies on the power produced by the conventional generators. Before the integration of renewable energies, the sum of the optimal power allocated to each thermal generator in 24 hours was 42674,08MW. A reduction to 37358,07MW, i.e., 12.45%, was optimized using the GTO method during the integration of renewable energies

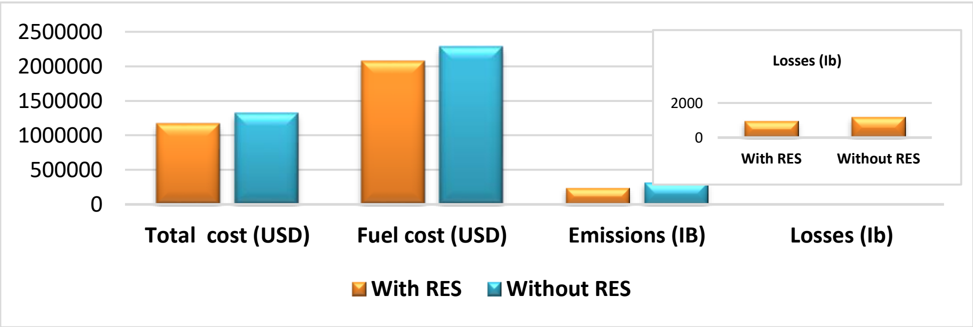

Figure 11. Comparaison of losses, Total cost, Fuel cost and emissions obtained by GTO with and without the ingration of RES

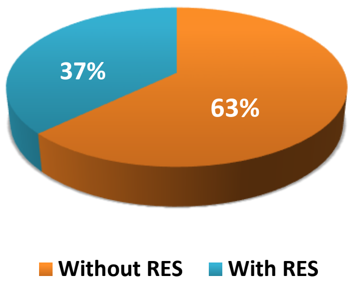

Figure 12. Comparison of Thermal Generator Power Output with and without Integration of Renewable Energy.

Table 4. Optimal results obtained by GTO for the case 4

PD(MW)	Total cost (USD)	Fuel cost (USD)	Emissions (IB)	Losses (Ib)	Constraints (MW)	Total gnerated power (MW)	Psolar (MW)	Pwind (MW)
1036	31045,1	57840,77	4190,702	18,9727	9,24E-14	150	0	20,25
1110	33542,91	62455,58	4589,788	21,828	2,60E-10	1131,828	0	13,95
1258	38214,25	70471,33	5920,199	28,0319	5,33E-14	1286,032	0	12,75
1406	42725,64	78148,5	7234,042	34,4778	1,42E-14	1440,478	0	23,7
1480	45202,21	82001,84	8354,727	38,8553	1,24E-08	1518,855	0	16,5
1628	50815,42	91023,25	10524,77	46,7169	3,48E-13	1674,717	0	28,56
1702	53370,1	94286,43	12300,09	50,8963	7,11E-14	1752,896	12,321	23,25
1776	53134,76	93422,03	12119,11	50,5985	1,52E-12	1825,599	95,721	17,7
1924	58231,44	100768,7	14622,84	56,9008	7,11E-15	1980,901	140,625	30
2022	58437,42	100416,5	14649,03	57,0815	0	2079,072	253,009	13,2
2106	55882,93	95750,74	13275,04	53,1051	7,11E-15	2159,095	380,689	25,95
2150	54430,62	93267,81	12250,53	50,667	7,74E-09	2200,668	470,596	16,8
2072	49936,08	86131,32	10223,96	44,0811	1,16E-11	2116.075	494,203	19,8
1924	42788,86	74510,45	7188,397	32,8657	1,49E-13	1956,866	541,696	30
1776	44091,93	78033,6	7659,488	35,5243	2,69E-11	1811,524	343,396	30
1554	41069,59	73862,77	6925,039	32,5291	6,39E-14	1586,529	180,625	30
1480	41838,12	76113,79	6895,73	33,8869	2,13E-13	1513,887	84,681	25,5
1628	50760,93	91266,88	10116,2	46,3784	0	1674,378	7,396	30
1776	58946,25	103600,2	14256,6	57,9334	7,11E-15	1833,933	0	12,3
1972	71008,98	123959,6	17971,38	72,4073	0	2044,407	0	30
1924	66946,12	116826	17009,66	69,0855	0	1993,086	0	19,5
1628	51809,57	92611,38	10970,36	48,0015	0	1676,002	0	12,9
1332	40067,79	73253,17	6827,599	31,1472	0	1363,147	0	18,9
1184	35152,2	64977,3	5272,288	24,4891	0	1208,489	0	18,9

Table 5. Optimal allocation of power among the ten generating thermal units

PG1 (MW)	**PG2 (MW)**	**PG3 (MW)**	**PG4(MW)**	**PG5(MW)**	**PG6(MW)**	**PG7(MW)**	**PG8(MW)**	**PG9(MW)**	**PG10(MW)**
150	**135**	114,9651	91,7409	194,3417	98,8863	113,5901	**70,6932**	37,4617	**28,0437**
150	**139,7612**	139,9679	104,4756	177,4387	148,8863	109,4994	**75,7822**	41,1751	**30,8917**
150	**146,7954**	149,3972	154,4756	227,4387	156,9727	107,829	**105,7822**	42,635	**31,9561**
150	**157,9307**	176,1342	204,4756	219,2164	159,9999	130	**111,7644**	72,635	**34,6215**
161,6376	**165,4472**	216,2178	201,8102	243	160	130	**120**	69,2425	**35**
171,1434	**173,3638**	261,8395	251,8102	243	160	130	**120**	80	**55**
174,4058	**176,408**	278,5114	300	243	160	130	**120**	80	**55**
174,7682	**176,7577**	285,7814	286,8702	243	160	130	**120**	80	**55**
189,6616	**192,6142**	340	300	243	160	130	**120**	80	**55**
190,8512	**194,0214**	340	300	243	160	130	**120**	79,99	**55**
177,0081	**178,9308**	318,9926	289,5362	242,9996	159,9989	130	**119,99**	80	**55**
172,8458	**174,8588**	300,5912	277,0188	243	159,9997	130	**120**	80	**54,9575**
156,0454	**161,7476**	262,2429	252,7352	236,7573	160	130	**120**	73,5839	**48,9598**
150	**135**	190,2103	208,7137	213,7033	153,7815	123,3307	**114,4958**	60,9444	**34,99**
150	**158,1622**	192,7935	195,9155	243	160	128,5087	**119,1888**	55,8661	**34,6933**
150	**151,3706**	180,1414	179,5683	226,6669	160	127,328	**118,9201**	49,0137	**32,8951**
150	**156,8431**	184,3101	172,0915	217,283	160	129,8676	**120**	79,0137	**34,2969**
180,2826	**182,2982**	264,3101	222,0915	243	160	130	**120**	80	**55**
205,824	**215,7179**	340	272,0915	243	160	130	**120**	80	**55**
245,0091	**341,3981**	340	300	243	160	130	**120**	80	**55**
234,1352	**311,4503**	340	300	243	160	130	**120**	80	**55**
154,1354	**231,4503**	260	261,1198	228,6974	160	130	**120**	70,8268	**46,8719**
150	**151,4503**	180	211,1198	196,1581	139,5738	118,3697	**109,7715**	54,7604	**33,0436**
150	**135**	139,3899	174,8088	173,1749	131,3815	110,6802	**103,2708**	42,9101	**28,9729**

Figure 13 illustrates the impact of forbidden zones on generators 2, 8, and 10. It is evident that these generators avoid operating within the prohibited regions, marked in pink. These restrictions are imposed due to issues related to system instability or physical limitations in the machinery. As a result, these zones introduce discontinuities in the fuel cost curve, as highlighted by the behavior of generator 2 when renewable energy is integrated into the system. Over the 24-hour period, generator 2 consistently avoids functioning within the two prohibited zones, ensuring stable and efficient operation despite these constraints.

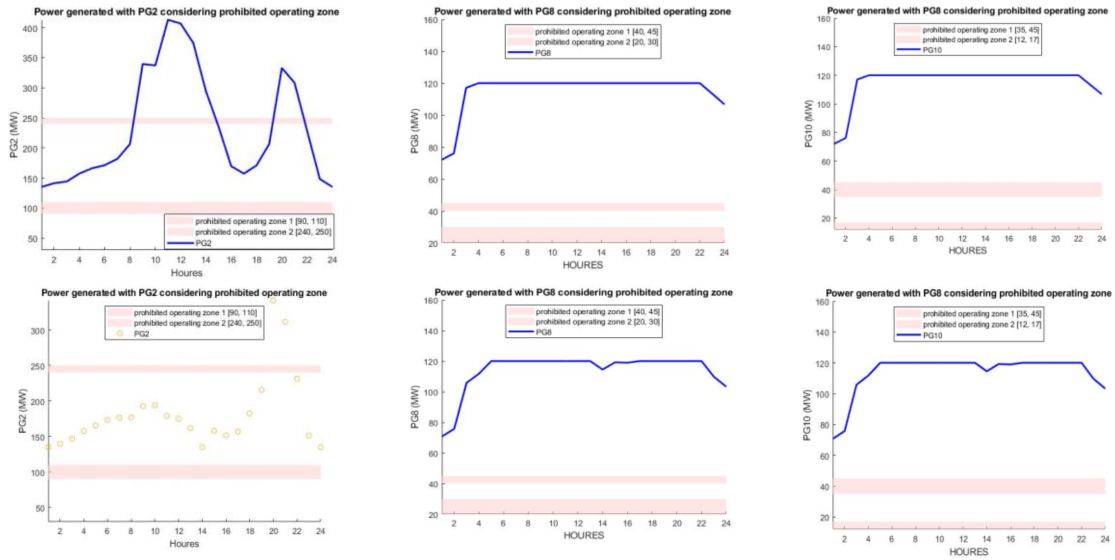

Figure 13. Prohibited operating zone limits on DCEED and HDCEED respectively with 10 generator cases.

Finally, to prove the rapidity and the robustness of the GTO algorithm for solving complex problem, Figure 14 shows the convergence of GTO case 4 of the hour 14 after multiple runs the GTO converge into the same value.

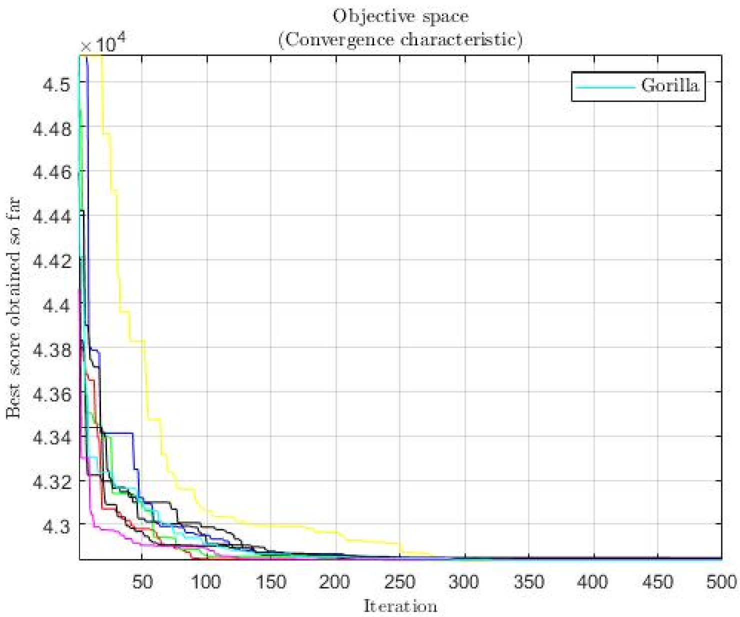

Figure 14. Convergence curve of multiple runs for case for at 14 o'clock

5. CONCLUSION

In this study, a new metaheuristic GTO tackles the complex problem of optimizing both economic and environmental dispatch with transmission losses and constraints, especially with the integration of variable wind and solar energy sources, despite challenges like valve effects, ramp rates , prohibited operating zone and dynamic system demands.

GTO has proven its superiority over other methods in terms of efficiency, speed, and reliability. Results across different test scenarios consistently show GTO's ability to generate competitive and optimal solutions comparing with other metaheuristics in term of minimization of fuel cost , emissions , transmission losses and operating cost, particularly if the scale of the problem increases. By integrating renewable energy sources, GTO significantly reduces fuel and total costs, emissions, and losses. Besides, GTO algorithm respects all equality and inequality constaints in all cases.

Future work aims to make the model even more realistic by accounting for uncertainties in wind and solar energy, while also optimizing surplus energy storage in batteries for enhanced system sustainability.

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