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Research Article

# Assessment of GTO: Performance Evaluation via Constrained Benchmark Function, and Optimized of Three Bar Truss Design Problem

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ABSTRACT

The aim of this paper is to show that the artificial gorilla troops optimization (GTO) algorithm, as an optimizer, can cope with test functions such as CEC2019, and also to best optimize the three bar truss design problem as a constrained optimization problem. As a method, two statistical measures such as the best values provided by the algorithms and the standard deviation showing the distance between the values were studied. At the same time, the convergence rate of the algorithms compared by the convergence curves were examined. For this purpose, it has been competed against two other swarm-based algorithms, sine-cosine algorithm (SCA) and golden eagle optimization (GEO). The optimization of the three bar truss design problem, which is another side of the study, has been made. The GTO algorithm reached the best values in the optimization of the parameters of the problem. In addition to the convergence curve, statistical results have examined, and the advantages of GTO are revealed through box-plot figures that evaluate the relationship between median and quartiles and the distribution among all results.

## Introduction

Truss bar optimization has become a very popular topic in recent years. Three bar truss (TBT) design problem, which is a classical engineering problem, can be defined as the process of finding the best parameters that give the minimum value of an objective function and also satisfy certain constraints [1, 2].

Why does it use metaheuristic algorithm? Because the metaheuristic algorithm's characterized like flexible structure, simple working because of non-derivative process, and don't suffer early converge which is ensure better optimizer than deterministic algorithm [3]. In the previous works have been studied on three bar truss design optimization problem optimized by metaheuristic algorithms [4-6]. While it has been demonstrated in this study that the artificial gorilla troops algorithm (GTO) is a competitive algorithm by testing it through the CEC2019 benchmark functions, the same results have been achieved with different functions in previous studies [7]. Real-world problem such as renewable energy source [8, 9], computer science [10], engineering optimization problems [11], power system stabilizer [12], industrial product design [13], and neural networks optimized [14] was solved with GTO algorithm and improved or hybrid variants of GTO at the used previous works. In this paper, three bar truss design problem will be discussed. Thus, the ability of the GTO algorithm to solve classic design problems will be revealed.

In this paper, the GTO algorithm is compared with the golden eagle optimizer (GEO) [15], sine cosine algorithms (SCA) [16], and harris hawks optimization (HHO) [17] which are also used in optimizing design problems [18-20]. In addition to these algorithms, the statistical results of the previously studied particle swarm optimization (PSO) and genetic algorithm (GA) classical algorithms were compared with the GTO algorithm [21].

This paper is including five sections. Firstly, section was by introduction, secondly section on introductory of problem, third section contain GTO's structure, fourth section competitional power of GTO via CEC2019, and optimize of problem. Finally, section is contained discussion and conclusions.

### Three bar truss design optimization problem

The aim of this problem is to design a truss structure that minimizes maximum node displacement without violating constraints such as buckling, stress, and bending, as shown in Figure 1 [1, 2, 21, 22].

Equation (1) will be optimized,

$$min f(x) = \left(2\sqrt{2}A_1 + A_2\right).l \tag{1}$$

$g_1, g_2$, and, $g_3$ are inequality constraints below that Equations (2-4) for Equation (1).

$$g_1 = \frac{2\sqrt{2}A_1 + A_2}{\sqrt{2}A_1^2 + 2A_1A_2} P \leq \sigma \quad (2)$$

$$g_2 = \frac{A_2}{\sqrt{2}A_1^2 + 2A_1A_2} P \leq \sigma \quad (3)$$

$$g_3 = \frac{1}{A_1 + \sqrt{2}A_2} P \leq \sigma \quad (4)$$

where

$$0 \leq A_1 \leq 1, 0 \leq A_2 \leq 1, l = 100cm,$$

$$\sigma = 2\, KN/cm^2\, , and\; P = 2\, KN/cm^2.$$

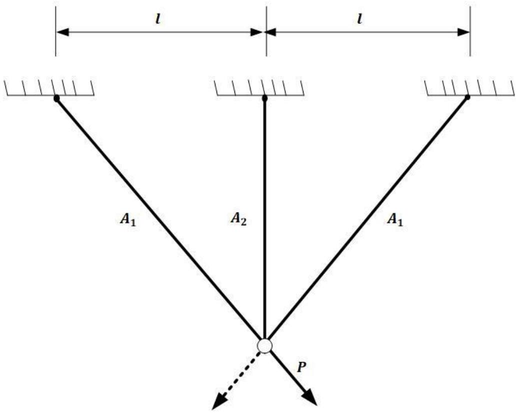


Figure 1. Three bar truss model [22]

## Gorilla Troops Algorithm

Artificial Gorilla Troops Algorithm (GTO) is a swarm-based algorithm based on leadership and community relationships in the community life of gorillas. The tasks of the male leader gorilla are to lead the swarm in many aspects such as defending against danger, finding food and making decisions. The swarm consists of male and female adult gorillas and offsprings. The mathematical modeling of the GTO metaheuristic algorithm, which is inspired by the swarm-based behavior of gorillas in their collective life in nature, consists of the following stages [7,10].

### Exploration (Diversification) phase

The gorilla troops are led by a gorilla called the silverback. In this regard, each candidate solution found is called a silverback solution. There are three main movements at this stage. For this, the position of the $p$ parameter is decisive and takes values between 0 and 1. The first movement refers to the movement towards the unknown when $k < p$, the second movement towards the group when $k \geq 0.5$, and the last movement to a known position when $k < 0.5$. Equation 1 expresses these three different situations in the exploration phase.

$$G(X_{new}) = \begin{cases} k_1 \times (ub - lb) + lb & k < p \\ X_k(k_2 - U) + V.R & k \geq 0.5 \\ X_i - V\big(V(X - GX_i) + k_3(X - GX_i)\big) & k < 0.5 \end{cases} \quad (5)$$

where $G(X_{new})$ indicates the candidate position vector of the gorilla at the next iteration, and X is the present vector of the gorilla [1]. $k, k_1, k_2$, and $k_3$ random values between 0 and 1. $ub$ and $lb$ indicates upper bound and lower bound of the variables, respectively. $X_i$ and $GX_i$ are random selected candidate position vectors in the group.

Equations (6), (7), and (8) calculate $U$, $V$, and $R$, respectively.

$$U = F\left(1 - \frac{iter}{Maxiter}\right) \quad (6)$$

$$F = cos(2t_4) + 1 \quad (7)$$

$$V = U.k \quad (8)$$

where $iter$ and $Maxiter$ indicates current iteration and maximum iteration, respectively. Initially, variation values will be generated over a wide range, while varying variation values will decrease towards the final optimization stage. $t_4$ and $k$ is a random value that is in interval [0,1]. Equation (6) display how to solving problem, and Equation (8) indicates silverback's leadership is simulated. $R$ in the Equation (1) is solved at Equation (9).

$$H = Z.X_k \quad (9)$$

$$Z = [-C, C] \quad (10)$$

At the end of the exploration phase, a group study covering all $GX$ solutions are conducted. If the cost is assumed to be $GX < X$, wrote $X$ instead of $GX$ and this best solution is considered silver back.

### Exploitation (Intensification) phase

During the exploitation phase of the GTO algorithm, two behaviors develop: following the lead gorilla, called the Silverback, and competing for adult females. The $U$ parameter is used for both tracking and competition. Using a w control parameter, $U \geq w$ will follow Silverback and $U < w$ will compete with females.

$$GX_{new} = V.m(\mathrm{X} - X_{silverback}\,)\,, U \geq w \quad (11)$$

$$m = \left(\left|\frac{1}{N\sum_{i=1}^{N} GX_i}\right|^q\right)^{\frac{1}{q}} \quad (12)$$

$$q = 2^V \quad (13)$$

$X$ is the vector of the silverback, $X_{silverback}$ is the vector of the silverback while the best location. $GX_i$ indicate is derived from to exploration phase to the vector position of each candidate gorilla at the present iteration. N indicates the sum of gorillas Equation (13) is also utilized to estimate q, and Equation (8) is also utilized to determine $V$ in Equation (13).

$$G(X_{new}) = X_{silverback} - (X_{silverback} - X)\Phi.a,\; U < w (14)$$

$$\Phi = 2.k_5 - 1 \quad (15)$$

$$A = \gamma.\theta \quad (16)$$

$$\theta = \begin{cases} N_1, & s \geq 0.5 \\ N_2, & s < 0.5 \end{cases} \quad (17)$$

where $\Phi$ refers to impact force, $k_5$ is a random variable from interval [0,1]. $A$ is coefficient vector that violence degree in conflict. A value must be assigned to parameter $\gamma$ before the optimization operation. $\theta$ is simulate the impact of force on the solution's dimensions. $s$ is a random variable from interval [0,1]. If $s$ is larger than or equal 0.5, $\theta$ is a random size from the normal distribution and the problem's bounds; if $s$ is less than 0.5, $\theta$ is a random value from the normal distribution.

**Experimental Conclusion**

The CEC2019 function was utilized for benchmarking algorithms. Performance assessment of the algorithms has been performed out using the challenging benchmark functions from CEC2019 test suite as shown that Table 1 [23]. This test set includes highly difficult and complex composition functions.

In this paper, GTO algorithm is compared with the GEO, SCA, HHO, PSO and GA algorithms. However, since GA and PSO algorithms are classically successful algorithms, the experimental results were taken from a different source, only the results were compared in Table 2, and the convergence curve was not drawn.

The MATLAB 2021 package program was used for benchmarking and quality testing of the algorithm, and each function was run 30 times to reach a fair solution. 500 iterations were performed using 30 search agents in each run.

When Table 2 is examined, it is seen the GTO algorithm which is the second algorithm after the PSO algorithm as a result of the F4 and F10 functions, and the second algorithm after the GA algorithm as a result of the F6 function, as well. For the F7 function, the GTO has achieved very good success, as can be seen in many different studies, since the problem of early convergence and local optimum has been observed [24]. In other functions except F4, F6 and F10, the GTO algorithm has achieved good success. As a result of all these experimental observations, it can be stated that GTO can be a competitive algorithm.

Whether the GTO algorithm has the problem of early convergence or local optima and its comparison with other algorithms can also be examined through convergence curves. In this context, when Figure 2 is observed, it will be seen that the GTO algorithm converges better than other algorithms.

500 iterations and 30 search agents were used to optimize TBT. A fair result was tried to be achieved with 30 independent runs. When the Table 3 is examined, it can be seen that all optimal values for TBT are provided by the GTO algorithm. When the Table 4 is examined, it can be observed that the GTO algorithm achieves the best result for the A2 parameter. On the other hand, it can be observed that the SCA algorithm is relatively more successful in optimizing the A1 parameter. However, when the box plot of the optimal values obtained as a result of independent runs is drawn in Figure 3, it can be observed that the GTO algorithm produces very close consistent values, while the SCA algorithm has both extreme values and the distance between the lowest result and the highest result is longer. In Figure 4, it can be observed that the GTO algorithm converges steadily, but the SCA algorithm suffers from early convergence and local optimum, while the GEO algorithm converges relatively late and cannot optimize TBT as much as the GTO algorithm.

Table 1. Parameters of CEC 2019

| Functions | Dimen sion | Bounds | Fitting Value |
|---|---|---|---|
| Storn's Chebyshev Polynomial Fitting Problem (F1) | 9 | [−8192, 8192] | 1 |
| Inverse Hilbert Matrix Problem (F2) | 16 | [−16384, 16384] | 1 |
| Lennard–Jones Minimum Energy Cluster (F3) | 18 | [-4,4] | 1 |
| Rastrigin's Function (F4) | 10 | [−100, 100] | 1 |
| Griewangk's Function (F5) | 10 | [−100, 100] | 1 |
| Weierstrass Function (F6) | 10 | [−100, 100] | 1 |
| Modified Schwefel's Function(F7) | 10 | [−100, 100] | 1 |
| Expanded Schafer's F6 Function (F8) | 10 | [−100, 100] | 1 |
| Happy Cat Function (F9) | 10 | [−100, 100] | 1 |
| Ackley Function (F10) | 10 | [−100, 100] | 1 |

Table 2. Superiority of GTO Algorithm

| F.no | Metric | GTO | GEO | SCA | HHO | PSO [21] | GA [21] |
|---|---|---|---|---|---|---|---|
| F1 | Best | **3.5580E+04** | 6.2980E+10 | 7.3504E+05 | 4.3994E+04 | 3.6316E+06 | 1.2909E+09 |
| | Std | **7.6777E+02** | 5.4913E+11 | 8.1749E+09 | 5.0620E+03 | 5.2101E+08 | 2.0443E+10 |
| | Rank | **1** | 6 | 3 | 2 | 4 | 5 |
| F2 | Best | **1.7343E+01** | 1.9210E+03 | 1.7401E+01 | 1.7350E+01 | 1.7343E+01 | 1.7359E+01 |
| | Std | **5.0593E-16** | 6.2141E+03 | 9.2037E-02 | 7.6000E-03 | 5.0593E-15 | 1.4505E+01 |
| | Rank | **1** | 6 | 5 | 3 | **2** | 4 |
| F3 | Best | **1.2702E+01** | 1.2703E+01 | 1.2702E+01 | 1.2702E+01 | 1.2702E+01 | 1.2702E+01 |
| | Std | **3.0336E-15** | 7.0309E-04 | 1.2331E-04 | 6.3218E-06 | 3.6134E-15 | 2.8453E-07 |
| | Rank | **1** | 6 | 5 | 4 | 2 | 3 |
| F4 | Best | 2.0894E+01 | 4.9688E+03 | 3.5718E+02 | 1.0431E+02 | **2.9849E+00** | 5.4231E+01 |
| | Std | 4.7402E+01 | 5.5859E+03 | 6.7346E+02 | 8.8490E+01 | **9.5931E+00** | 4.8556E+01 |
| | Rank | 2 | 6 | 5 | 4 | **1** | 3 |
| F5 | Best | **1.0123E+00** | 3.2463E+00 | 2.0538E+00 | 1.4616E+00 | 1.0271E+00 | 1.0800E+00 |
| | Std | **6.4709E-02** | 8.3273E-01 | 9.1901E-02 | 05.725E-01 | 8.6000E-02 | 1.0100E-01 |
| | Rank | **1** | 6 | 5 | 4 | 2 | 3 |
| F6 | Best | 4.1927E+00 | 1.1034E+01 | 9.7940E+00 | 7.3419E+00 | 5.4320E+00 | **3.5465E+00** |
| | Std | 1.2005E+00 | 9.1232E-01 | **6.3686E-01** | 1.0071E+00 | 1.4167E+00 | 8.2840E-01 |
| | Rank | 2 | 6 | 5 | 4 | 3 | **1** |
| F7 | Best | **3.0353E+01** | 1.0779E+03 | 3.7643E+02 | 9.4918E+01 | -6.4755E+01 | -1.5598E+02 |
| | Std | **1.4287E+00** | 2.1711E+02 | 1.9093E+02 | 2.2215E+02 | 1.0307E+02 | 1.5239E+02 |
| | Rank | **1** | 6 | 5 | 3 | 2 | 4 |
| F8 | Best | **2.8489E+00** | 6.4394E+00 | 5.3351E+00 | 4.5395E+00 | 3.2864E+00 | 3.3511E+00 |
| | Std | 9.3211E-01 | **3.6854E-01** | 4.2444E-01 | 4.9910E-01 | 7.5560E-01 | 7.4110E-01 |
| | Rank | **1** | 6 | 5 | 4 | 2 | 3 |
| F9 | Best | **2.3368e+00** | 1.1325E+03 | 2.1582E+01 | 2.6864E+00 | 2.3430E+00 | 2.5288E+00 |
| | Std | 1.2978e-01 | 8.1371E+02 | 1.0718E+02 | 6.2550E-01 | **1.3400E-02** | 3.2930E-01 |
| | Rank | **1** | 7 | 6 | 4 | 2 | 3 |
| F10 | Best | 2.0133e+00 | 1.7165E+01 | 2.0277E+01 | 2.0033E+01 | **1.9644E-11** | 2.7150E+00 |
| | Std | 3.2835e+00 | 5.8992E-01 | **1.0435E-01** | 1.1980E-01 | 3.6939E+00 | 3.1609E+00 |
| | Rank | 2 | 4 | 6 | 5 | **1** | 3 |

Table 3. Optimal value ($minf(x)$) of TBT

| Algorithms | Metrics | | | |
|---|---|---|---|---|
| | Mean value | Minimum value | Std. Dev. value | Rank |
| GEO | 2.6395E+02 | 2.6395E+02 | 8.3691E-02 | 4 |
| SCA | 2.6851E+02 | 2.6390E+02 | 8.0421E+00 | 6 |
| HHO | 2.6402E+02 | 2.6390E+02 | 1.8426E-01 | 5 |
| GTO | **2.6389E+02** | **2.6389E+02** | **3.2661E-06** | **1** |
| PSO [21] | 2.6390E+02 | 2.6390E+02 | 5.3917E-05 | 2 |
| GA [21] | 2.6391E+02 | 2.6390E+02 | 2.5206E-02 | 3 |

| Algorithms | Parameters | | Rank | |
|---|---|---|---|---|
| | A1 | A2 | A1 | A2 |
| GEO | 7.8910E-01 | 4.0710E-01 | 4 | 2 |
| SCA | **6.1311E-01** | 6.1178E-01 | **1** | 4 |
| HHO | 7.8847E-01 | 4.0883E-01 | 2 | 3 |
| GTO | 7.8867E-01 | **4.0630E-01** | 3 | **1** |

Table 4. Optimal value parameters of TBT

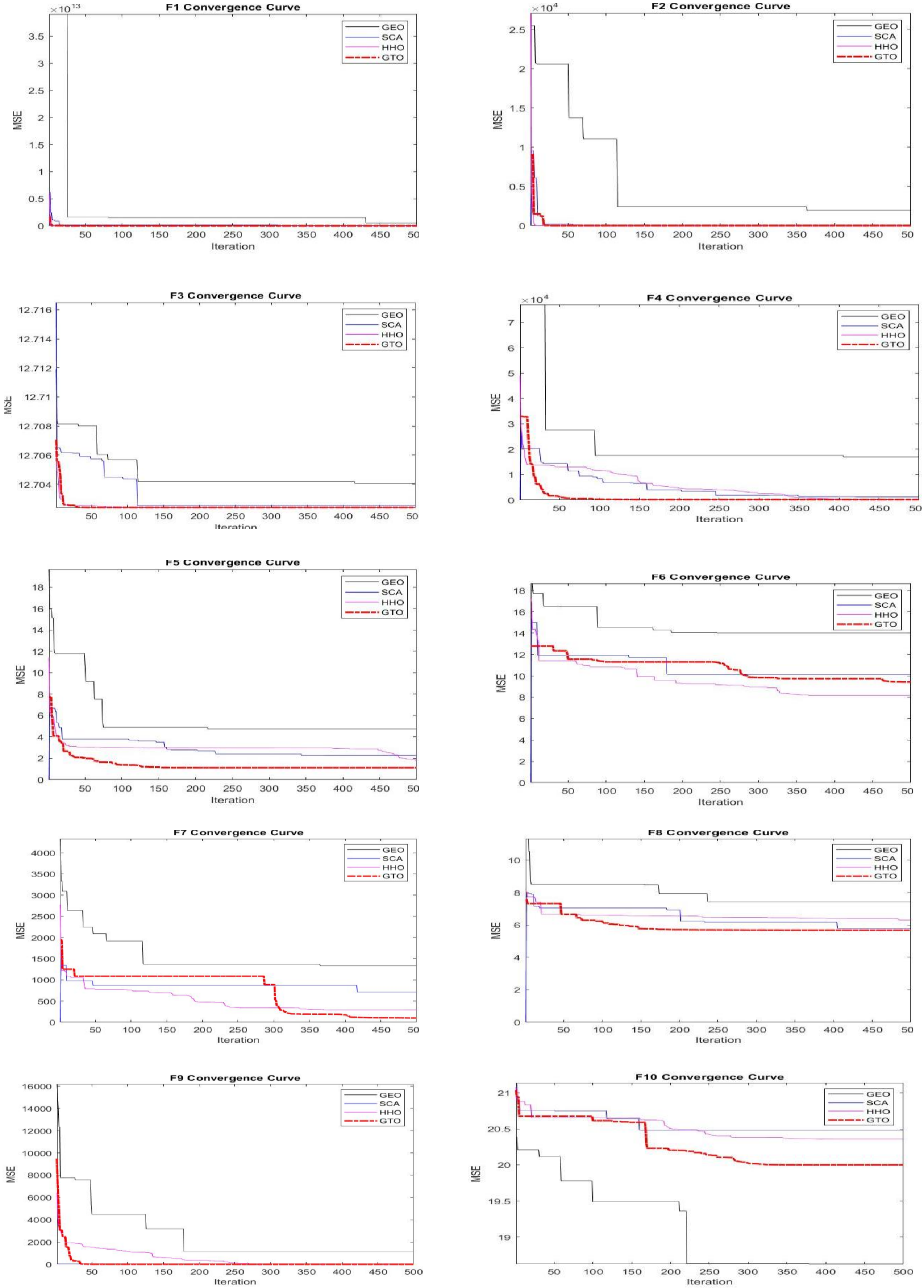

Figure 2. Convergence curve of F1-F10 functions

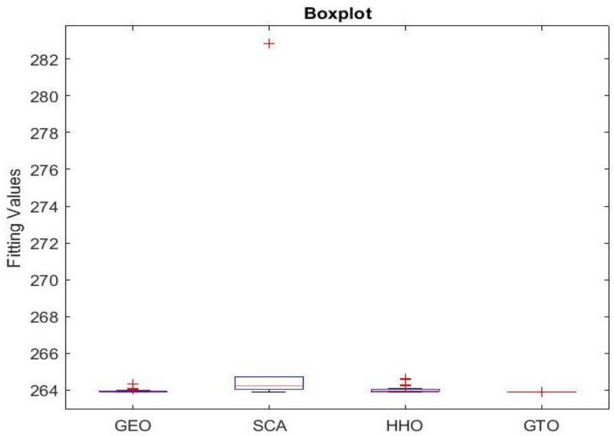

Figure 3. Boxplot of TBT

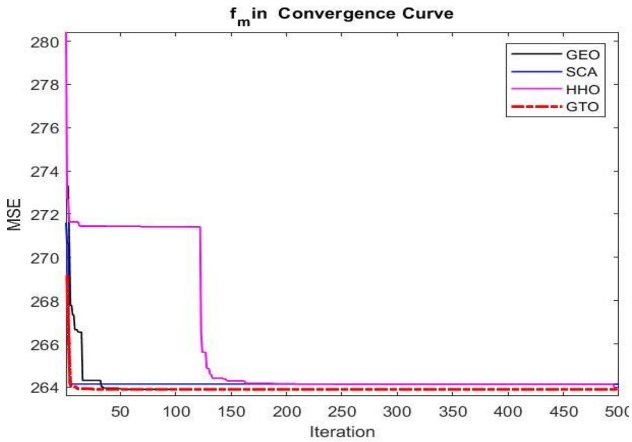

Figure 4. Converge curve of TBT

**Conclusion**

In this study, it was observed that the GTO algorithm successfully optimized the CEC2019 test set. In the light of statistical measurements, it has been shown that the GTO algorithm can compete with the swarm-based SCA and GEO algorithms selected from different areas, the classical PSO and GA algorithms, and the HHO algorithm, one of the contemporary algorithms. It has been observed that the GTO algorithm can more successfully optimize TBT, which is one of the constrained design optimization problems, by competing with other algorithms in the presence of statistical measurements. Despite its recent introduction to the literature, it has been tried to observe that GTO is a modern metaheuristic algorithm that has been successful in many different areas. Successful results can be obtained in many areas by applying different strategies to develop the GTO algorithm.

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