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RESEARCH PAPER

A Novel Enhanced Gorilla Troops Optimizer Algorithm for Global Optimization Problems

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ABSTRACT

Researchers in many fields, such as operations research, computer science, AI engineering, and mathematical engineering, are increasingly adopting nature-inspired metaheuristic algorithms because of their simplicity and flexibility. Natural metaheuristic algorithms are based on two essential terms: exploration (diversification) and exploitation (intensification). The success and limitations of these algorithms are reliant on the tuning and control of their parameters. When it comes to tackling real optimization problems, the Gorilla Troop Optimizer (GTO) is an extremely effective algorithm that is inspired by the social behavior of gorilla troops. Three operators of the original GTO algorithm are committed to exploration, and the other two operators are dedicated to exploitation. Although the superiority of GTO algorithm over several metaheuristic algorithms, it needs to improve the balance between the exploration process and the exploitation process to ensure an accurate estimate of the global optimum. For this reason, a Novel Enhanced version of GTO (NEGTO), which focuses on the correct balance of exploration and exploitation, has been proposed. This paper suggests a novel modification on the original GTO to enhance the exploration process and exploitation process respectively, through introducing a dynamic controlling parameter and improving some equations in the original algorithm based on the new controlling parameter. A computational experiment is conducted on a set of well-known benchmark test functions used to show that NEGTO outperforms the standard GTO and other well-known algorithms in terms of efficiency, effectiveness, and stability. The proposed NEGTO for solving global optimization problems outperforms the original GTO in most unimodal benchmark test functions and most multimodal benchmark test functions, a wider search space and more intensification search of the global optimal solution are the main advantages of the proposed NEGTO.

KEYWORDS: *Metaheuristics; Nature-inspired algorithms; Gorilla troop optimization algorithm; Global optimization problems.*

1. Introduction

Metaheuristics are powerful optimization algorithms for treating and solving complex real-life stochastic problems as well as numerical problems. Conventional algorithms for solving such practical everyday problems are time-consuming and often do not yield exact or feasible solutions. Therefore, it is necessary to move from conventional techniques to standard metaheuristic techniques inspired by nature. Hyper-simulation techniques are capable of intelligently using search experience to explore and exploit random search spaces and imprecise and near-optimal solution methods. In metaheuristics techniques, a near-optimal solution or good solution is obtained through the balance between the essential two phases of any metaheuristic algorithm, which are addressed by exploration (diversification) and exploitation (intensification) [1].

GTO is proposed by [2] which is a recently proposed metaheuristic algorithm based on the simulation of the social behavior of gorilla troops. It is used for solving several problems successfully, such as a hybrid microgrid system

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[3], Power System Stabilizer [4, 5], photovoltaic models [6-9], Localization of Wireless Sensor Networks[10], Renewable distributed generators [11], Intrusion Detection Systems [12], Wind Farm Integrated Deregulated Power System [13], High-Dimensional Optimization Problems [14], and global optimization [15].

GTO was inspired by gorillas' social intelligence and collective lifestyle. According to preliminary research, GTO performs extremely well when used to optimize benchmark functions. Like other meta-heuristic algorithms, it still has low optimization accuracy, converges too quickly, and tends to get stuck in the local optimum when solving complex optimization problems. A lack of proper balance between exploration and exploitation, as well as a low likelihood of large spatial leaps in the iteration process, are the most common causes of these issues. Consequently, we are motivated to improve this latest swarm-based algorithm [6].

A NEGTO is proposed in this paper, which aims to enhance the balance of the trade-off between exploration and exploitation in the standard GTO. The GTO algorithm's parameters can be tuned using a variety of functions with different slopes, allowing for a wide range of exploration and exploitation combinations. Convergence speed is increased by increasing exploration in comparison to exploitation, which avoids the trapping effect of local minima.

The remainder of the paper is as follows: A brief description of the original GTO is described in Section 2. Section 3 introduced the proposed NEGTO. In Section 4, the comparison of the experimental results is illustrated. Eventually, Section 5 concludes the paper.

2. The Standard Gorilla Troops Optimizer Algorithm

The GTO is one of the recent swarm intelligence algorithms inspired by the lifestyle and social behaviors of gorillas, which live in groups known as troops, which consist of an adult male or silverback, several adult females, and their offspring. A silverback's name is derived from the silver-colored hair that develops on its back during puberty. Male gorillas tend to leave their groups and form new ones by attracting females who have already migrated, which is how they form new groups. The silverback group is made up of male gorillas who occasionally stay with the group to which they were born. Gorilla females build deep bonds with males to ensure a successful mating season and to safeguard their own safety from predators. Without silverback gorillas to protect infant gorillas, infant gorillas may fall victim to infanticide and seek to join new groups as a solution. Silverback is the focal point of the group. It makes all decisions, mediates conflicts, determines group movements, guides gorillas to food sources, and is responsible for the group's safety and well-being. Blackbacks are young male gorillas that follow silverbacks and provide backup protection for the group.

The standard GTO, as shown in Fig. 1 and Section 2.1, is mathematically based on five operators that mimic the behaviour of gorillas: three different operators for exploration and two different operators for exploitation.
operators for exploitation [2].

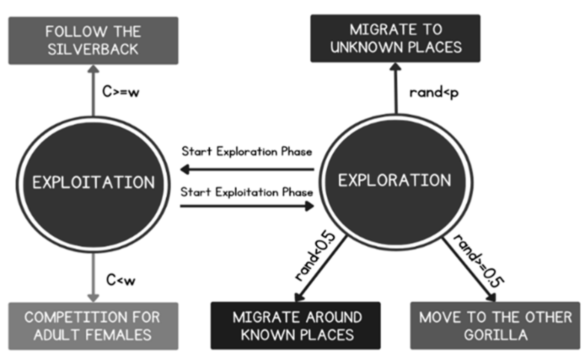

Fig. 1. Optimization operations of GTO [2]

2.1. Mathematical model operators

- Increasing GTO exploration through the migration to anonymous areas.
- Increasing the balance between both exploration and exploitation through moving to other gorillas.
- Increasing the search space capability through the movement towards a known place.
- Following the silverback leads to continued and systematic exploration maintaining to facilitate exploitation.
- Competition for adult females, which mimics the group expansion and fighting process by

puberty gorillas.

The first three phases represent the exploration strategy, which is formulated mathematically as follows:

$$gx_i(t+1) = \begin{cases} (r_1 \times (U^b - L^b) + L & rand < p, \\ x_i(t) - L \times (x_i(t) - gx_r(t)) + r_3 \times (x_i(t) - gx_r(t)), & p < rand < 0.5, \\ (r_2 - C) \times x_r(t) + L \times H & rand \geq 0.5 \end{cases} \quad (1)$$

where $gx_i(t+1)$ represent the next iteration value of candidate gorilla, r_1, r_2, r_3, U^b, L^b, are random numbers between [0,1], upper bound and lower bound respectively, $x_r(t)$ is the current iteration random gorilla, $x_i(t)$ is the *i*-th gorilla in the current iteration, and $gx_r(t)$ is the current iteration value of candidate gorilla. p is a parameter applied to select the migration mechanism to an anonymous location. In Eq. (2), Eq. (3), and Eq. (4), the values of $C, L, and\ H$ are calculated.

$$C = \left(1 - \frac{t}{tMax}\right) \times F \quad (2)$$

Where t, $tMax$ are the current iteration and the maximum iteration respectively, $F = cos(2 \times r_4) + 1$.

$$L = C \times rand(-1,1) \quad (3)$$
$$H = x(t) \times rand(-C, C) \quad (4)$$

After the exploration phase, the fitness values of candidate gorillas and gorillas are compared. If a current gorilla is worse than a candidate gorilla, the current gorilla is removed from the population, and the candidate gorilla turns into a gorilla in the population.
The fitness values of candidate and current gorillas are compared at the end of the exploration process. If the fitness value of the current gorilla is worse than the candidate gorilla's fitness value, the current gorilla is uninvolved in the new population and the candidate gorilla will be considered a silverback (best solution).
The last two phases are modelled in two mathematical functions to represent the exploitation process as follows.

$$gx_i(t+1) = L \times \left(\left|\frac{1}{N}\sum_{i=1}^{N} gx_i(t)\right|^{\frac{1}{2L}}\right) \times (x_i(t) - x_{SB}(t)) + \times (x_i(t) - x_i(t)) \quad (5)$$

where $x_{SB}(t)$ is the gorilla silverback (the best gorilla in the current iteration), N is the number of the population, and $gx_i(t)$ is the candidate gorilla value in the current iteration.

$$gx_i(t+1) = x_{sb}(t) - ((2r_5 - 1) \times x_{sb}(t) - (2r_5 - 1) \times x_i(t)) \times \beta \times \begin{cases} N_1, rand \geq 0.5 \\ N_2, rand < 0.5 \end{cases} \quad (6)$$

Where r_5 is a random number between [0,1], β is a constant value, N_1, N_2 are random normal distribution values vector.
At the end of the exploitation process, the fitness values of candidate and current gorillas are compared. If the fitness value of the current gorilla is worse than the candidate gorilla's fitness value, the current gorilla is uninvolved in the new population and the candidate gorilla will be considered a silverback (best solution). The standard GTO pseudo code is illustrated as in Fig 2.

Initialize the input parameters: Maximum number of iterations $MaxIt$, search agent population (gorilla troops) $x_i(i = 1,2, \dots N)$, and the parameters $p = 0.03, \beta = 3$, and $w = 0.8$.
Calculate the fitness value of the search agent gx
While ($t < tMax$**)**
Exploration phase using Equations (1),(2),(3), and (4)
Calculate the gorilla fitness value
If $(gx > x)$
reset gx as a new x
end if
Set the best solution x_{sb} as a location of silverback
Exploitation phase using Eq. (5) and Eq. (6)
Calculate the gorilla fitness value
If $(gx > x)$
reset gx as a new x

end if
Set the best solution x_{sb} as a location of silverback
End while
Return **silverback** (best location) and best **fitness value**

Fig. 2. The standard pseudo code of the GTO [2]

3. A Novel Enhanced GTO Algorithm

Achieving the best balance between both exploration and exploitation operations to accomplish the near-optimal solution is a challenging task among nature-inspired algorithms. Similar to nature-inspired techniques, the stability and the accuracy of convergence of GTO will be stuck in a local optimum by solving optimization problems more flexibly and more complexly. So, the motivation of the proposed NEGTO is to overcome these defects and to enhance the performance of exploration and exploitation operations.

In the original GTO, the parameter $w = 0.8$ is a controlling parameter to switch between two exploitation mechanisms, either using equation (5) if $c >= w$ or using Eq. (6) if $c < w$.In the proposed MGTO, to make a search space wider in exploration process, and to intensify the search in the exploitation process, a NEGTO uses the parameter w in different optimization operations to become an online parameter based on the number of iterations instead of a constant value.

$$w = 1 - \left(2 \times e^{-\left(\frac{4\times t}{tMax}\right)^{t}}\right) \tag{7}$$

Furthermore, the parameter L in Eq. (4) represents the leadership of the silverback, which is reformulated based on the parameter w.

$$L = C \times (C \times rand - w)^{\frac{t}{w}} \tag{8}$$

The proposed NEGTO is modified with the second exploration mechanism in Eq. (1) by multiplying the parameter w if $rand \geq 0.5$.

$$gx_i(t+1) = \begin{cases} (r_1 \times \left(U^b - L^b\right) + L & rand < p, \\ x_i(t) - L \times \left(x_i(t) - gx_r(t)\right) + r_3 \times \left(x_i(t) - gx_r(t)\right), & p < rand < 0.5, \\ (r_2 - C) \times x_r(t) + L \times H \times w & rand \geq 0.5. \end{cases} \tag{9}$$

4. Computational Experiments

4.1. Mathematical model operators:

For the purpose of verifying the efficiency of the proposed MGTO, fifteen benchmark test functions are used. Unimodal functions, multimodal functions, and fixed-dimension multimodal are three different categories of benchmark functions that are used in this paper, as shown in Tables 1-3.

Tab. 1. Unimodal benchmark test functions

Function	Dim	Range	f_{min}
$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[-100,100]	0
$f_2(x) = \sum_{i=1}^{n} \lvert x_i\rvert + \prod_{i=1}^{n} \lvert x_i\rvert$	30	[-100,100]	0
$f_3(x) = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_j\right)^2$	30	[-100,100]	0
$f_4(x) = max_i\{\lvert x_i, 1 \leq i \leq n\rvert\}$	30	[-100,100]	0
$f_5(x) = \sum_{i=1}^{n} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-30,30]	0
$f_6(x) = \sum_{i=1}^{n-1} ([x_i + 0.5])^2$	30	[-100,100]	0
$f_7(x) = \sum_{i=1}^{n} ix_i^4 + rand[0,1]$	30	[-1.28,0]	0

Tab. 2. Multimodal benchmark test functions

Function	Dim	Range	f_{min}
$f_8(x) = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	30	[-500,500]	-418.982×5
$f_9(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	30	[-5.12,5.12]	0
$f_{10}(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n} cos\,(2\pi x_i)\right) + 20 + e$	30	[-32,32]	0
$f_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30	[-600,600]	0
$f_{12}(x) = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n}(y_i - 1)^2[1 + 10sin^2(\pi y_{i+1})] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m x_i > a \\ 0 \quad -a < x_i < a \\ k(-x_i - a)^m x_i < -a \end{cases}$	30	[-50,50]	0
$f_{13}(x) = 0.1\{sin^2(3\pi x_i) + \sum_{i=1}^{n}(x_i - 1)^2[1 + sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + sin^2(2\pi x_n)]\} + s\sum_{i=1}^{n} u(x_i, 5, 100, 4)$	30	[-50,50]	0

Tab. 3. Fixed-dimension multimodal benchmark test functions

Function	Dim	Range	f_{min}
$f_{14}(x) = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}\right]^2$	2	[-5,5]	0.00030
$f_{15}(x) = 4x_1^2 - 2.1x_1^2 + \frac{1}{3}x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^2$	4	[-5,5]	-1.0316

4.2. Mathematical model setting of parameters

For the sake of performance evaluation of NEGTO, we conduct a comparison with the original GTO which is superior to several metaheuristic algorithms such as particle swarm optimization algorithm, whale optimization algorithm, grey wolf optimizer, moth-flame optimizer, gravitational search algorithm, sine cosine algorithm, Tunicate swarm algorithm, and Multi□verse optimizer. A comparison between the performance of GTO and NEGTO is implemented with 50 independent runs for each benchmark function, 30 population size, and 200 maximum iterations for each run. A four performance evaluation metrics are used to measure the NEGTO performance, including the best fitness value, worst fitness value, average fitness value (mean), and the standard deviation of optimization solutions.

Tab. 4. Comparison between GTO results and NEGTO results on unimodal benchmark test functions

F	GTO				NEGTO			
	Best	Worst	Mean	STD	Best	Worst	Mean	STD
f_1	8.21E-172	3.10E-153	6.23E-155	4.34E-154	4.09E-237	1.90E-198	5.70E-200	0.00E+00
f_2	9.47E-88	6.19E-75	2.42E-76	9.82E-76	1.97E-118	1.57E-96	3.14E-98	2.22E-97
f_3	1.89E-165	1.27E-140	5.16E-142	2.33E-141	2.59E-223	6.15E-185	1.23E-186	0.00E+00
f_4	4.63E-85	2.55E-72	5.10E-74	3.60E-73	3.57E-115	3.36E-96	7.48E-98	4.77E-97
f_5	6.02E-06	2.73E+01	1.15E+01	1.31E+01	5.94E-10	2.74E+01	6.40E+00	1.15E+01
f_6	8.70E-07	1.06E-02	1.33E-03	2.08E-03	4.29E-10	1.50E-01	4.58E-03	2.17E-02
f_7	1.20E-05	1.20E-03	2.81E-04	2.48E-04	4.36E-06	3.52E-01	7.25E-03	4.98E-02

Tab. 5. Comparison between GTO results and NEGTO results on multimodal benchmark test functions

F	GTO				NEGTO			
	Best	Worst	Mean	STD	Best	Worst	Mean	STD
f_8	-1.91E+03	-1.91E+03	-1.91E+03	0.00E+00	-1.91E+03	-1.91E+03	-1.91E+03	0.00E+00
f_9	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
f_{10}	8.88E-16	8.88E-16	8.88E-16	5.98E-31	8.88E-16	8.88E-16	8.88E-16	5.98E-31
f_{11}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
f_{12}	1.22E-08	1.20E-03	1.05E-04	1.84E-04	2.52E-11	1.19E-03	4.94E-05	1.77E-04
f_{13}	1.99E-07	5.06E-02	3.71E-03	8.85E-03	4.14E-09	3.08E-02	1.66E-03	5.65E-03

Tab. 6. Comparison between GTO results and NEGTO results on fixed-dimension multimodal benchmark test functions

F	GTO				NEGTO			
	Best	Worst	Mean	STD	Best	Worst	Mean	STD
f_{14}	9.01E-04	2.21E-03	1.03E-03	1.72E-04	3.08E-04	2.21E-03	1.01E-03	5.27E-04
f_{15}	-1.03E+00	-1.03E+00	-1.03E+00	4.49E-16	-1.03E+00	-1.03E+00	-1.03E+00	4.49E-16

As listed in Tables 4-6, the presented results demonstrate the superiority of NEGTO to GTO and hence to the other previous algorithms that were compared to GTO by Abdollahzadeh et al[2]. We can summarize the comparison between NEGTO and GTO in several points:

- The proposed NEGTO is superior to GTO in all the unimodal benchmark test functions from $f_1$to f_7.
- The proposed NEGTO is superior to GTO in three multimodal benchmark test functions ($f_{12}, and\ f_{13}$).
- The proposed NEGTO gives the same results as GTO in five multimodal benchmark test functions ($f_8, f_9,\ f_{10},\ and\ f_{11}$).
- The proposed NEGTO also gives a better result in f_{14}, and the same result in f_{15}

From the previous points, we can conclude that the GTO is easily trapped in the local optima due to the premature convergence and the NEGTO overcomes these defects. Thus, the results demonstrated that the proposed NEGTO enhanced the capabilities of both exploration and exploitation operations.

According to [16], the movement of search agents should change abruptly during the initial stages of optimization. This allows a meta-heuristic to thoroughly explore the search space. Then, at the end of optimization, these changes should be reduced to emphasize exploitation. As seen in (Figures 3-5), in the initial iterations steps the NEGTO makes abrupt change which is decreased progressively over the set of iterations.

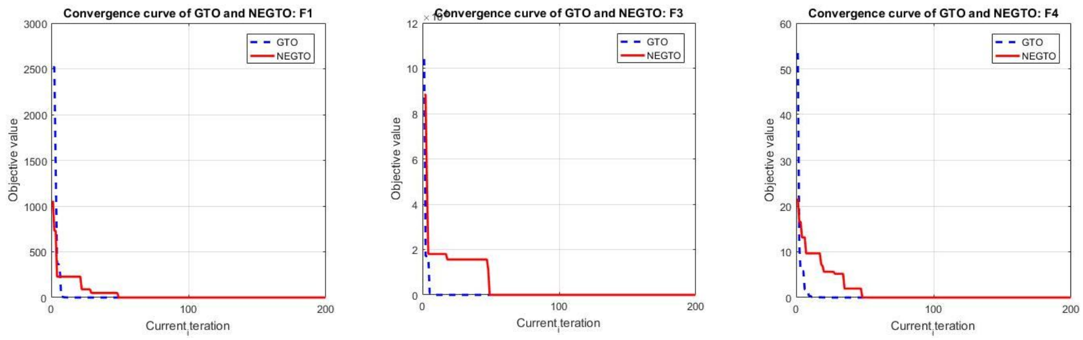

Fig. 3. Convergence curves of GTO and NEGTO on (f_1, f_3, f_4) unimodal benchmark functions

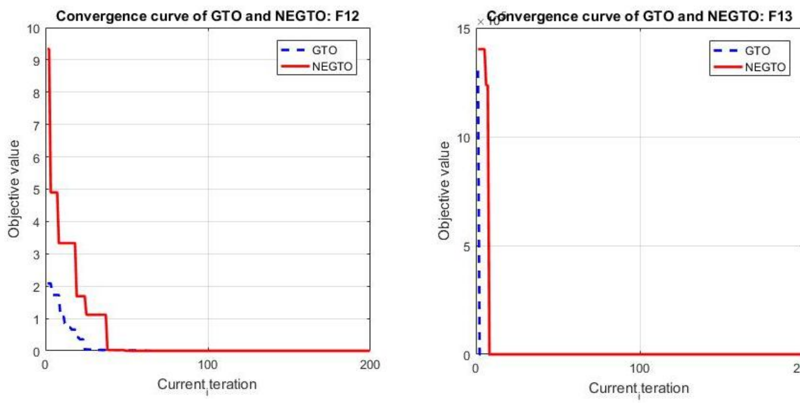

Fig. 4. Convergence curves of GTO and NEGTO on (f_{12}, f_{13}) multimodal benchmark functions

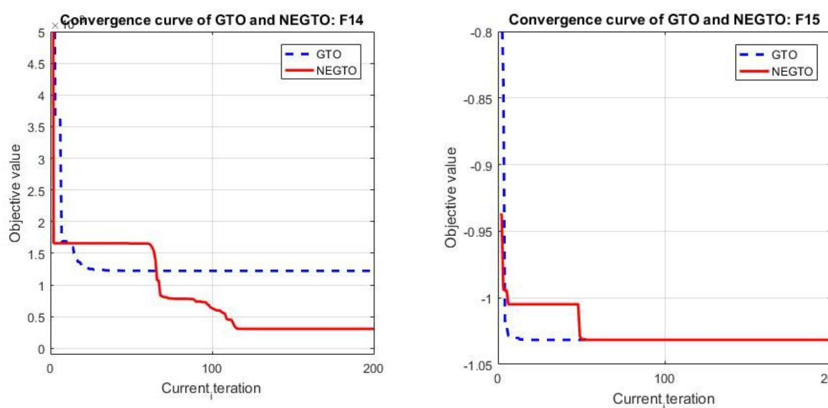

Fig. 5. Convergence curves of GTO and NEGTO on (f_{14}, f_{15}) fixed-dimension multimodal benchmark functions

5. Conclusion

In this paper, a new modification of GTO named NEGTO is introduced. A dynamic function is used instead of a constant value of the parameter. Furthermore, another two modifications are conducted in the exploration mechanism function in case the random number is greater than 0.5, and function (4) represents a silverback leadership. To compare the efficiency of the proposed NEGTO algorithm to GTO, 15 benchmark test functions, including unimodal benchmark functions, multimodal benchmark functions, and fixed-dimension multimodal benchmark functions are used. The metrics of performance evaluation prove the superiority of NEGTO to GTO either in the quality of solution or the characteristics of convergence, hence the superiority of NEGTO to other algorithms that were compared with GTO in the literature review. The results show that the proposed NEGTO is an effective tool for solving different optimization problems.

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