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Critical Analysis of Various Varients on Electric Eel Foraging Optimization (EEFO)

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Abstract: In this paper the Electric Eel Foraging Optimization (EEFO) algorithm was developed with inspiration from the way electric eels hunt for food. These eels perceive their environment and locate prey by producing electric fields. By imitating this natural behaviour, EEFO similarly looks for the optimal answer in an optimization problem. The algorithm cleverly strikes a compromise between exploitation (enhancing the best options discovered) and exploration (looking for new alternatives). This facilitates EEFO's more effective resolution of challenging issues. It works effectively and frequently outperforms conventional techniques in tests on various optimization tasks. EEFO's speed and precision make it a valuable tool for artificial intelligence, engineering, and other domains that require intelligent problem-solving

Keywords: EEFO, Benchmarks Functions, Nature Based Algorithm, Levy Flight, Optimization.

1. Introduction

In several domains, including artificial intelligence, engineering, and healthcare, optimization issues are prevalent. In order to address these issues, researchers employ nature-inspired metaheuristic algorithms. Electric Eel Foraging Optimization (EEFO) is one such algorithm that is based on the way electric eels seek and move through their surroundings.

To analyze its environment and identify the optimum solutions, EEFO makes use of the eel's electrolocation abilities. This feature aids the algorithm in striking a balance between exploitation (concentrating on the best locations) and exploration (searching extensively). As a result, EEFO works well for resolving various kinds of optimization issues. The EEFO algorithm is examined in this paper along with its operation and comparison to other optimization methods. We also consider strategies to enhance EEFO by integrating it with techniques such as random walks and chaotic maps. The findings demonstrate that EEFO does a good job of quickly identifying high-quality solutions.

2. Literature Review

EEFO is a newer bio-inspired optimization method that mimics how electric eels sense their surroundings. Unlike traditional algorithms, EEFO adapts dynamically, using an electric field-based sensing approach to find better solutions. This makes it useful for a wide range of optimization problems.

To improve EEFO, recent studies have suggested combining it with other techniques. Overall, EEFO is a promising optimization technique. Its unique sensing-based approach allows it to balance searching and refining solutions efficiently. Future research should focus on improving EEFO further through hybrid methods, better parameter tuning, and real-world applications.

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Fig 1. Classification of Metaheuristic Algorithm.

Author Table:

Reference No.	Algorithm Name	Author Name	Year
1	Fruit Fly Optimization	W. Y. Lin	2016
2		Y. Cheng et al	2018
3	Hybrid Ant Colony	X. Wang et al	2018
4	Global Optimization	I.E. Grossmann	1996
5		R. V. Rao et al	2016
6	Grey Wolf Optimization	M.El-Kenawy	2020
7	Particle Swarm Optimization	M. Nouiri et al	2018
8	Multi-objective Optimization	Y. Li et al	2018
9	Harris Hawks Optimizer	D.Yousri et al	2020
10	Genetic Programming	R. Al-Hajj et al	2017
11	Evolutionary Computing	R. Al-Hajj et al	2016
12	Classical & non-classical	R.A. Meyers	2000
13	Quadratic Programming	N. Steffan at al	2012
14	Grasshopper Optimization	M. Mafarja et al	2018
15	Water Cycle	A. A. Heidari et al	2017

Table 1. Literature Revie

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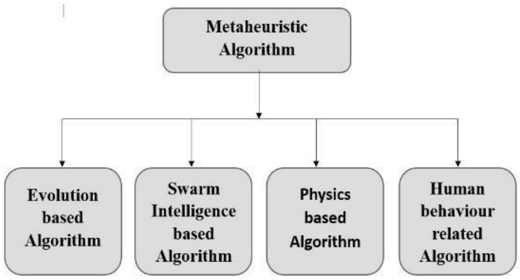

Functions	Dimensions	Range	f_{min}
$F_1(S) = \sum_{m=1}^{z} S_m^2$	(10,30,50,100)	[-100 , 100]	0
$F_2(S) = \sum_{m=1}^{z} \lvert S_m \rvert + \prod_{m=1}^{z} \lvert S_m \rvert$	(10,30,50,100)	[-10 ,10]	0
$F_3(S) = \sum_{m=1}^{z} (\sum_{n-1}^{m} S_n)^2$	(10,30,50,100)	[-100 , 100]	0
$F_4(S) = max_m \{\lvert S_m \rvert, 1 \le m \le z\}$	(10,30,50,100)	[-100 , 100]	0
$F_5(S) = \sum_{m=1}^{z-1} [100(S_{m+1} - S_m^2)^2 + (S_m - 1)^2]$	(10,30,50,100)	[-38 , 38]	0
$F_6(S) = \sum_{m=1}^{z} ([S_m + 0.5])^2$	(10,30,50,100)	[-100 , 100]	0
$F_7(S) = \sum_{m=1}^{z} m S_m^4 + random\ [0,1]$	(10,30,50,100)	[-1.28, 1.28]	0

Functions	Dimension	Range	f_{min}
$F_8(S) = \sum_{m=1}^{z} - S_m sin(\sqrt{\lvert S_m \rvert})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z} [S_m^2 - 10cos\ (2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp\ (-0.2 \sqrt{\left(\frac{1}{z} \sum_{m=1}^{z} S_m^2\right)}) - exp\ (\frac{1}{z} \sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(10,30,50,100)	[-32,32]	0
$F_{11}(S) = 1 + \sum_{m=1}^{z} \frac{S_m^2}{4000} - \Pi_{m=1}^{z} cos \frac{S_m}{\sqrt{m}}$	(10,30,50,100)	[-600, 600]	0
$F_{12}(S) = \frac{\pi}{z} \left\{10\, sin(\pi \tau_1) + \sum_{m=1}^{z-1} (\tau_m - 1)^2 [1 + 10 sin^2(\pi \tau_{m+1})] + (\tau_z - 1)^2 \right\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_{m+1}}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(10,30,50,100)	[-50,50]	0
$F_{13}(S) = 0.1\{sin^2(3\pi S_m) + \sum_{m=1}^{z} (S_m - 1)^2 [1 + sin^2(3\pi S_m + 1)] + (x_z - 1)^2 [1 + sin^2 2\pi S_z)]$	(10,30,50,100)	[-50,50]	0

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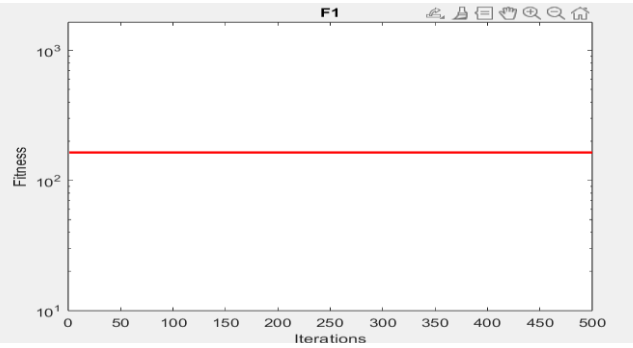
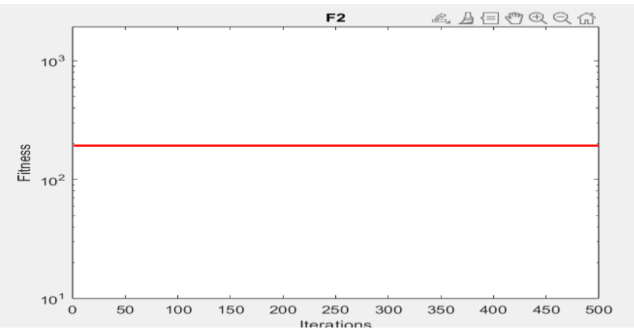
Functions	Dimensions	Range	f_{min}
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5 \frac{1}{n+\sum_{m=1}^{2}(S_m - b_{mn})6}]^{-1}$	2	[-65.536, 65.536]	1
$F_{15}(S) = \sum_{m=1}^{11} [b_m - \frac{S_1(a_m^2 + a_m S_2)}{a_m^2 + a_m S_3 + S_4}]^2$	4	[-5, 5]	0.00030
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1 S_2 - 4S_2^2 + 4S_2^4$	2	[-5, 5]	-1.0316
$F_{17}(S) = (S_2 - \frac{5.1}{4\pi 2}S_1^2 + \frac{5}{\pi}S_1 - 6)^2 + 10(1-\frac{1}{8\pi})cosS_1 + 10$	2	[-5, 5]	0.398
$F_{18}(S) = [1+(S_1+S_2+1)^2(19-14S_1+3S_1^2-14S_2+6S_1S_2+3S_2^2)] \times [30+(2S_1-3S_2)^2(18-32S_1+12S_1^2+48S_2-36S_1S_2+27S_2^2)]$	2	[-2,2]	3
$F_{19}(S) = -\sum_{m=1}^{4} d_m exp(-\sum_{n=1}^{3} S_{mn}(S_m - q_{mn})^2)$	3	[1, 3]	-3.32
$F_{20}(S) = -\sum_{m=1}^{4} d_m exp(-\sum_{n=1}^{6} S_{mn}(S_m - q_{mn})^2)$	6	[0, 1]	-3.32
$F_{21}(S) = -\sum_{m=1}^{5}[(S-b_m)(S-b_m)^T + d_m]^{-1}$	4	[0,10]	-10.1532
$F_{22}(S) = -\sum_{m=1}^{7}[(S-b_m)(S-b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.4028
$F_{23}(S) = -\sum_{m=1}^{7}[(S-b_m)(S-b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.5363

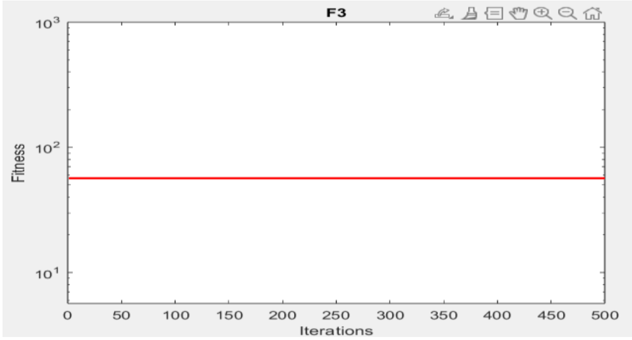
Table 2. Standard UM Benchmark Functions.

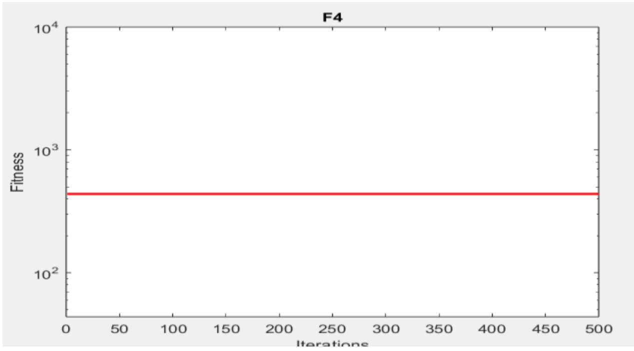
3. Result and Discussion

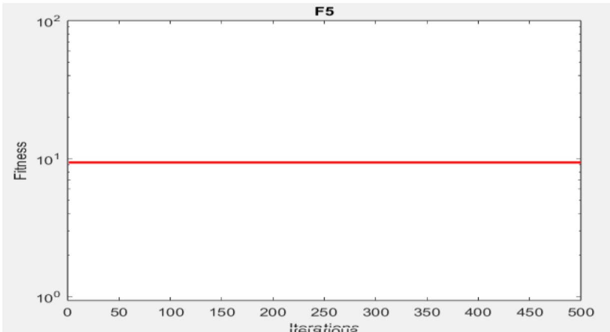
In this method we test EEFO on 23 benchmark functions. After that we hybridized EEFO with PSO, Levy Flight and Random Walk algorithms. We find convergence curves which are given below.

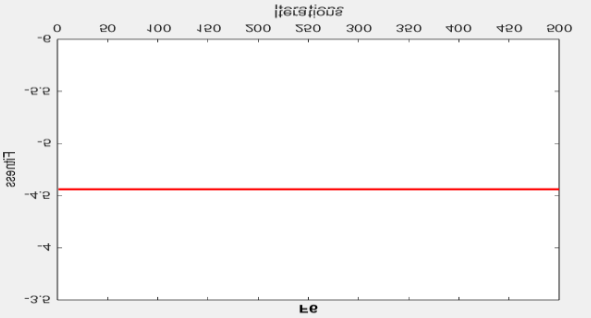


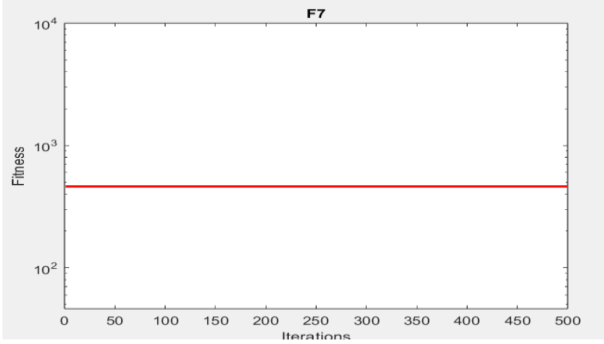












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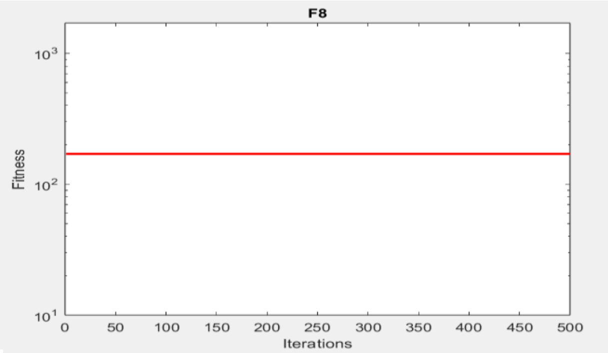

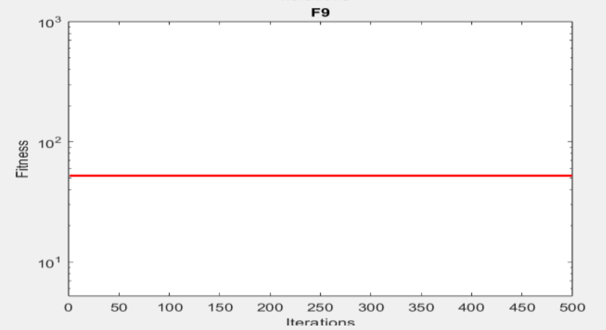

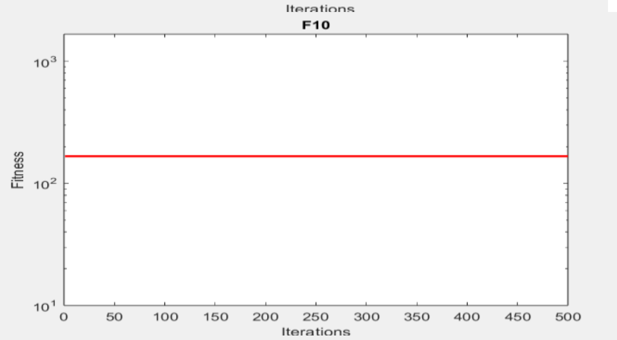

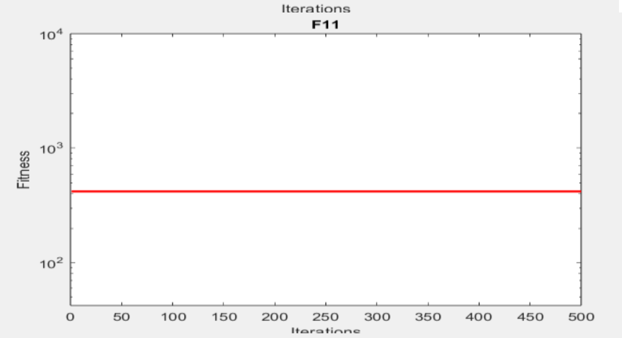

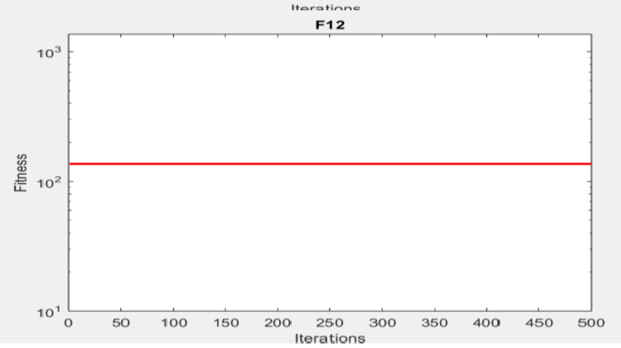

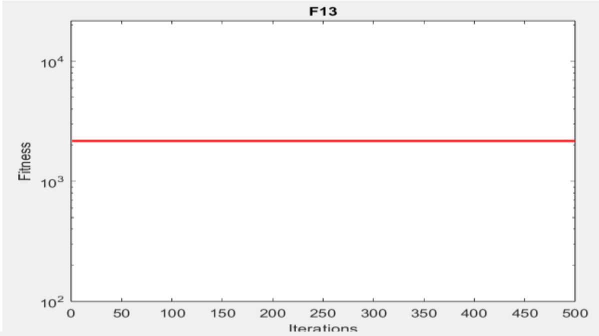

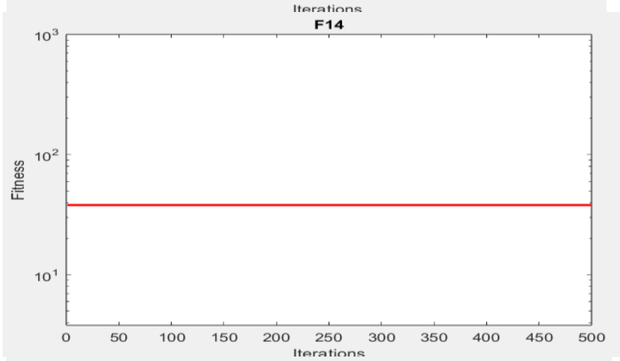

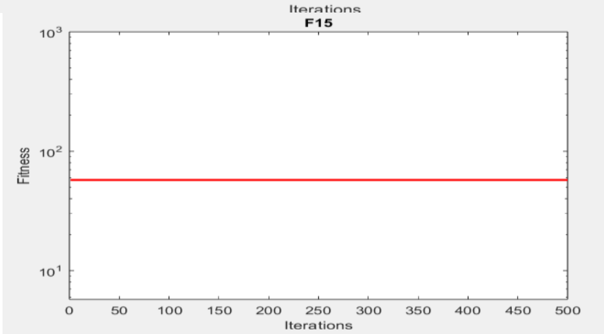

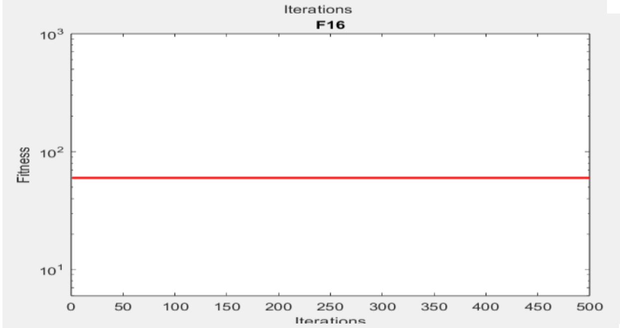

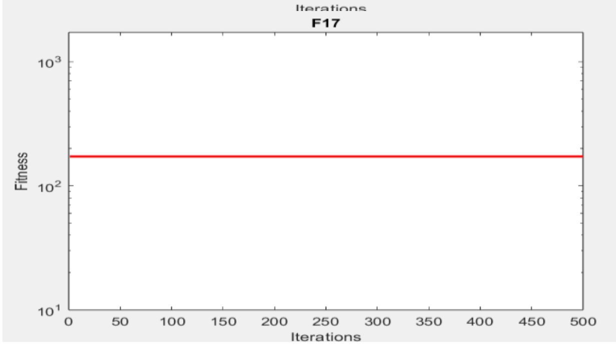

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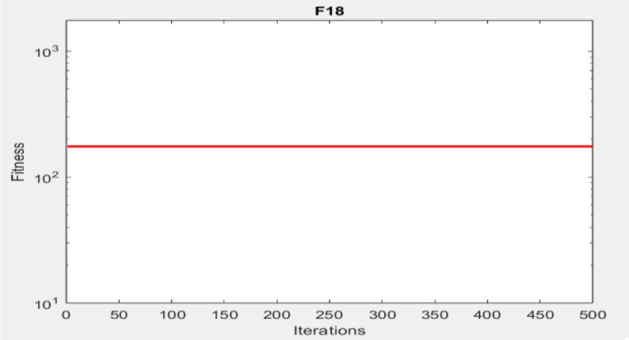

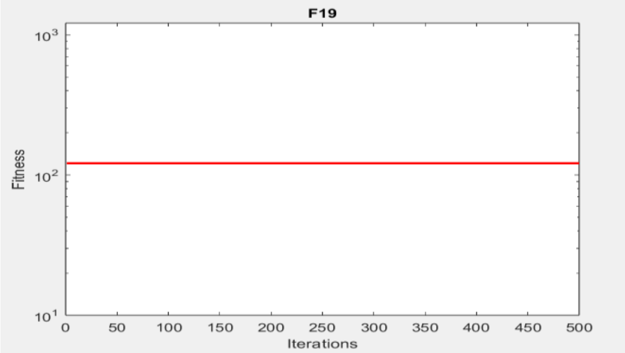

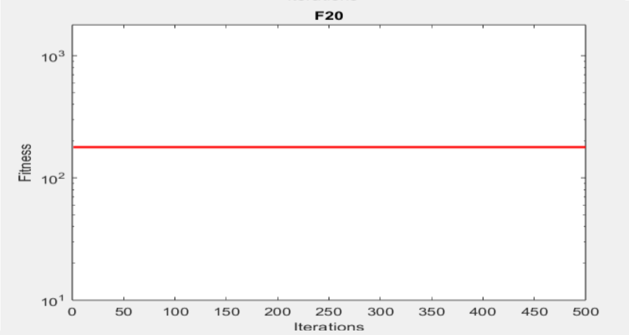

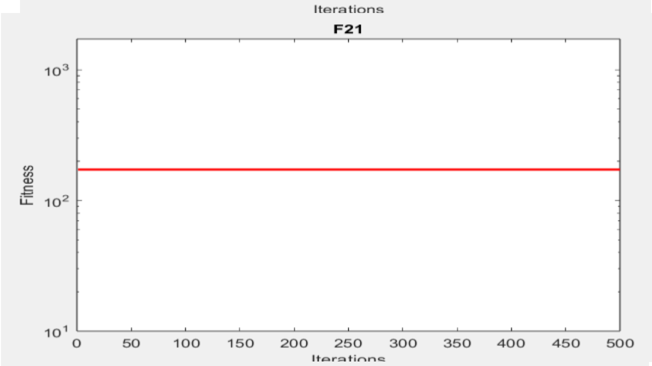

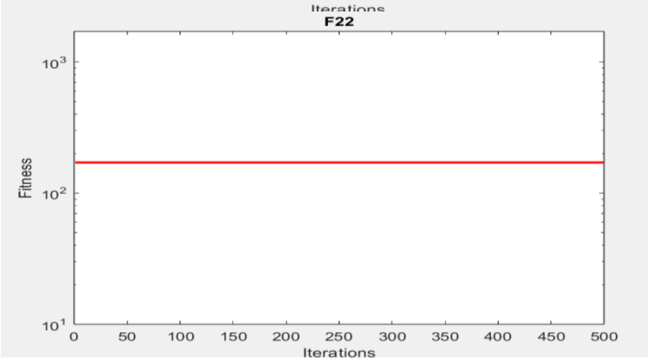

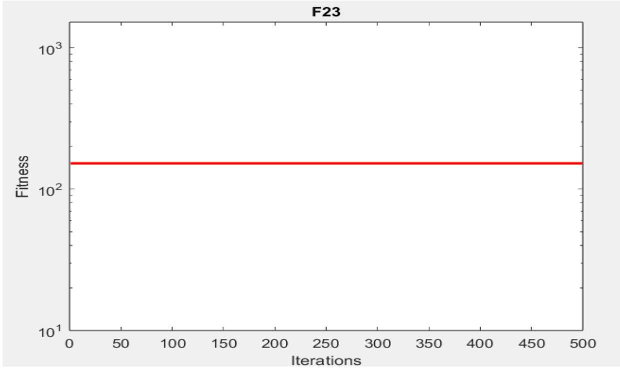

Fig 1: Search Space for Benchmark Functionsapplied on EEFO

Result Table:

Function Number	Original Values	Hybridization With PSO	Levy Flight	Random Walk
F1	4.2542e-295	3.2481e-07	170.0354	3.811
F2	7.3462e-144	0.00038508	157.0354	3.1091
F3	4.0273e-225	0.064555	60.9453	2.8153
F4	8.6014e-139	122.384	443.721	4.6698
F5	1.4226e-15	-2123.721	8.5768	2.3792
F6	0	-13.1609	-3.9301	3.2052
F7	0.00026489	117.531	432.4288	4.8472
F8	-12569.486	8.8474	176.3214	3.9423
F9	0	0	55.1024	2.2359
F10	4.4409e-16	-3463.4461	171.6601	4.4823
F11	0	1.0238e-05	469.535	1.1581
F12	1.5705e-32	0.00035141	163.3278	4.2016
F13	1.3498e-32	95.5174	2008.4029	3.146
F14	0.998	-189.0139	38.5834	3.2164
F15	0.00030749	57.7953	54.3422	2.7988
F16	-1.0316	0.0043073	60.6357	2.2497
F17	0.39789	4.7886e-06	183.7034	3.7102
F18	3	0.013283	184.1282	2.4885
F19	-3.8628	11.1639	181.1282	3.2526
F20	-3.322	0.00035443	167.7936	3.6727
F21	-10.1532	0.92232	159.4758	3.2679
F22	-10.4029	-2010.6882	161.0753	3.4028
F23	-10.5364	-3463.6684	165.7671	4.0258

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Table 3. Results for Original EEFO vs Hybrid EEFO with PSO, Levy Flight, Randomwalk.

5. Conclision

Electric Eel Foraging Optimization (EEFO) algorithm was hybridized with PSO, Levy Flight, and Random Walk algorithm and each hybridized algorithm was tested on 23 benchmark functions out of which it did not performs better in any of the above hybridized approaches. By observing the results, we conclude that the original algorithm itself performs better and provides the optimal value or best solution for all 23 benchmark functions (F1-F23).

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