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Enhancing the Zebra Optimization Algorithm with Chaotic Sinusoidal Map for Versatile Optimization

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ABSTRACT In this study, the Chaotic Sinusoidal Map (CSM)-enhanced Zebra Optimization Algorithm (CZOA) is introduced. CZOA combines CSM's integration strengths with ZOA's optimization skills. ZOA already exhibits great optimization capabilities, but the addition of CSM increases its potential even more. This addition greatly strengthens ZOA's exploration and exploitation skills and increases its flexibility for various optimization tasks. CZOA outperforms both the original ZOA and contemporary optimisation methods on 23 benchmark functions, including high-dimensional (FD), multimodal (MM), and unimodal (UM) challenges. Using the chaos of CSM to investigate regional optimal and determine better convergence and exploration-exploitation equilibrium are shown by CZOA, which also shows more profitable solution locations. CZOA demonstrates its resilience and versatility through multiple benchmark activities, underscoring its potential as an adaptable optimisation tool. CZOA becomes a potent metaheuristic by combining biological inspiration and chaotic dynamics to solve difficult optimisation problems. Inspired by the natural behaviour of zebras, the Zebra Optimisation Algorithm (ZOA) is a relatively new optimisation technique. It makes use of a herd behaviour mechanism and the ideas of leadership and following, in which members of the population—zebras in this case—cooperate to solve optimisation issues in the best possible ways.

A chaotic sinusoidal map can improve the ZOA's exploitation and exploration capabilities, increasing its adaptability for optimisation across a range of problem domains.The success of CZOA and its potential as a potent

1. INTRODUCTION

The complexity of optimization issues is rising as science and technology develop and production capacity increases. It has become vital to find effective solutions for these challenging issues. The development of metaheuristic algorithms offers a viable method for addressing optimization issues. They draw their inspiration from natural evolutionary rules, which have evolved over thousands of years in order to increase survival and promote population growth.

The complexity of optimization issues is rising as science and technology develop and production capacity increases. It has become vital to find effective solutions for these challenging issues. The development of metaheuristic algorithms offers a viable method for addressing optimization issues. They draw their inspiration from natural evolutionary rules, which have evolved over thousands of years in order to increase survival and promote population growth.

To overcome challenging issues, researchers have studied these natural processes and created algorithms. In this approach, the optimization issue is abstracting into the best population-inspired solution, the living environment serves as the abstract search space, and the behavior of each member of the population represents a set of solutions. As in the case of the Harris hawks optimizer (HHO) [1], The intricacy of optimisation problems is increasing in tandem with scientific and technological advancements and increased production capacity. It is now essential to identify workable answers for these difficult problems. Creating metaheuristic algorithms provides a workable way to deal with optimisation problems. Natural evolutionary laws, which have developed over thousands of years to boost survival and encourage population development, serve as their source of inspiration. Researchers have examined these natural processes and developed algorithms to solve difficult problems. This method uses the living environment as the abstract search space, the behaviour of each member of the population as a set of solutions, and the optimisation problem as an abstraction into the best population-inspired solution. the Harris Hawks Optimizer (HHO) [1], for example-Numerous issues, including complicated engineering problems, neural networks, shortest route optimization, feature selection, and power scheduling , have been effectively solved using these effective and reliable techniques.

Sheikholeslami et al. [8] demonstrated that a sufficiently random sequence is necessary to ensure better performance in the algorithm's global search phase, particularly for metaheuristic algorithms that simulate and make decisions for complex natural phenomena. Metaheuristic algorithms are capable of solving optimization problems in large-scale search spaces. Metaheuristic methods must include population initialization. It directly affects the effectiveness of the algorithm's search and the caliber of the outcome. Therefore, in order to more effectively address real-world issues, academics have been looking at different strategies to enhance population initialization. One of the most popular metaheuristic initialization techniques is randomized initialization, which builds a population by generating search space solutions at random. One of the best methods for creating a suitably random and evenly dispersed starting sequence for metaheuristic algorithms is to employ chaotic maps. Numerous optimization issues have been addressed by fusing chaotic maps with metaheuristic methods. For instance, in 2023 praveen et al. [9] suggested a faster version of the arithmetic method, while in 2017 Arora et al. [10] suggested leveraging chaos to enhance the butterfly algorithm. The investigations described above have produced promising experimental findings. For limited situations, Kohli et al. [11] chaotic gray wolf optimization algorithm was introduced, and testing showed how efficient it is. Jia et al. [12] demonstrated the viability of a chaotic local search approach by using chaos theory to differential evolution.

Studies on chaotic-based ZOA algorithms are not currently being conducted. Previous studies have shown that combining chaotic maps with metaheuristic techniques has successfully addressed a variety of optimization problems. As a result, we suggest the chaotic-Sinusoidal map-based zebra optimization algorithm, or CZOA, to the best of our understanding. 23 benchmark test functions are used to evaluate the proposed algorithm's performance in order to get the best results from CZOA. In the meantime, a serious issue with the power generation forecast is included for assessment.

2. LITERATURE REVIEW

Metaeuristic algorithms are created using various factors of nature, human behavior, swarms, and games. A few of them are discussed in Table 1 with their motivation.

Table 1: recent metaheuristic search strategies and their motivation

Ref & year	Algorithm	Motivation
[13]& 2023	Squid Game Optimizer SGO	Korean game
[14]& 2023	Waterwheel Plant Algorithm	waterwheel plant’s
[15]& 2023	Spider wasp optimizer	female spider wasps
[16]& 2023	Zebra Optimization Algorithm	Zebras
[17]& 2023	Mother optimization algorithm	Mother and her children's interaction
[18]& 2023	hermit crab optimization	Hermit crabs
[19]& 2023	Orchard Algorithm	fruit gardening
[20]& 2023	Eagle perching optimizer	eagles’ perching
[21]& 2023	American zebra optimizer	American zebra’s
[22]& 2023	Sparrow Search Optimizer	Sparrows
[23]& 2023	Drawer Algorithm	Different drawers
[24]& 2023	Subtraction-Average-Based Optimizer	Mathematical operators
[25]& 2023	Osprey optimization algorithm	Ospreys

[26]& 2020	Slime mould algorithm	Slime mould
[27]& 2023	Energy valley optimizer	particle decay
[28]& 2023	Green Anaconda Optimization	Green anaconda
[29]& 2023	Exponential distribution optimizer	exponential probability distribution's
[30]& 2023	Nutcracker optimizer	Nutcrackers
[31]& 2023	Coronavirus Mask Protection optimizer	Covid-19

The unique and unusual sources of inspiration for optimization strategies are where the literature gap in the presented algorithms is found. This unconventional strategy highlights the necessity to investigate and assess these unique sources of inspiration' applicability and efficacy across multiple optimization problem domains. It also creates a vacuum in our knowledge of how they contribute to efficient optimization tactics.

The lack of available literature on unorthodox optimization approaches influenced by various real-world elements creates the requirement for chaotic CZOA implementation. There hasn't been much research on adding chaotic dynamics into the Zebra Optimization Algorithm, despite the fact that many algorithms take inspiration from unusual sources including animals, Covid-19 protection, and more. CZOA may improve the algorithm's exploration and exploitation capabilities, tackling difficult optimization problems in many issue areas. The unique strategy of CZOA tries to fill this gap by incorporating chaos and biological inspiration, providing a viable path for developing optimization tools.

MATHEMATICAL MODELING OF ZOA

Zebras, equine creatures from eastern and southern Africa, are known for their black and white fur and large size. They have long, thin legs and exhibit foraging and predator defense behaviors, with zebras fleeing in zigzags to terrify predators [16].

Zebras are part of the population of ZOA, a population-based optimizer. A matrices may be used to represent the zebra population numerically. The zebras are first placed in a random location inside the search area. Equation (1) specifies the ZOA population matrices.

Table 2: ZOA parameters

Z	zebra population	$z_{i,j}^{new,P1}$	jth dimension value
Z_i	ith zebra	PZ_j	jth dimension
$z_{i,j}$	jth problem variable proposed by the i^{th} zebra	PZ	pioneer zebra which is the best member
N	No. of population zebra's	r	random number in interval [0, 1]
m	No. of decision variable's	$F_i^{new,P2}$	objective function value
$Z_{i,j}^{new,P2}$	jth dimension value	$F_i^{new,P1}$	objective function value
$Z_i^{new,P2}$	new status of the ith zebra based on second phase	AX_j and AZ	jth dimension value and attacked zebras
I	I is the round (1 + rand), rand is [0, 1]. Thus, I ∈ {1, 2}	R and Ps	constant number equal to 0.01 and randomly generated in [0, 1].
T, and t	maximum number of iterations and iteration contour	$Z_i^{new,P1}$	new status of the ith zebra based on first phase

$Z = \begin{bmatrix} Z_1 \\ \cdots \\ Z_i \\ \cdots \\ Z_N \end{bmatrix}_{N*m} = \begin{bmatrix} z_{1,1} & z_{1,j} & z_{1,m} \\ z_{i,1} & z_{i,j} & z_{i,m} \\ z_{N,1} & z_{N,j} & z_{N,m} \end{bmatrix}_{N*m}$	(1)

Every zebra represents a possible solution to the optimization problem. Therefore, one may evaluate the objective function by utilizing the suggested values of each zebra for the problem variables. The values obtained for the objective function are given as a vector using equation (2).

$F = \begin{bmatrix} F_1 \\ F_i \\ F_N \end{bmatrix}_{N*1} = X = \begin{bmatrix} F(Z_1) \\ F(Z_i) \\ F(Z_N) \end{bmatrix}_{N*1}$	(2)

where F is the zebra's achieved aim and F is the objective vector.

PHASE 1: Foraging Behavior Depending on the type and amount of vegetation, zebras may feed for 60–80% of their total time. ZOA refers to the best population member as the pioneer zebra, who points other members of the population in the direction of its location inside the search space. Consequently, it is possible to quantitatively forecast how zebras' positions will vary during the foraging phase by utilizing equations (3) and (4).

$z_{i,j}^{new,P1} = z_{i,j} + r.(PZ_j - I.z_{i,j})$	(3)
$Z_i^{new,P2} = \begin{cases} S_1 : z_{i,j} + R.(2r-1) \\ (1-\frac{t}{T}).z_{i,j}, \quad Ps \le 0.5; \\ S_2 : z_{i,j} + r.(AX_j - I.z_{i,j}), else, \end{cases}$	(4)

Phase Two: Predator Defense Techniques

Lions, cheetahs, leopards, wild dogs, brown hyenas, and spotted hyenas are among the predators that pose a threat to zebras. When they get close the water, they also run into crocodiles. Zebras become more combative when they are attacked by smaller predators. Either an aggressive plan of action or an escape path is predicted by the ZOA design.

$Z_{i,j}^{new,P2} = \begin{cases} S_1 : z_{i,j} + R.(2r-1) \\ (1-\frac{t}{T}).z_{i,j}, \quad Ps \le 0.5; \\ S_2 : z_{i,j} + r.(AX_j - I.z_{i,j}), else, \end{cases}$	(5)
$Z_i = \begin{cases} Z_i^{new,P2}, F_i^{new,P2} < F_i; \\ Z_i, \quad else, \end{cases}$	(6)

In the first tactic, when lions attack zebras, the zebras abandon the region where they are placed to avoid the lion's onslaught. This strategy can be mathematically represented by the mode S1 in (5). When other predators attack one of the zebras in an attempt to scare and confound the predator by creating a protective structure, the other zebras in the herd migrate towards the attacking zebra in the second technique. Equation (5) uses the mode S2 to numerically represent the behavior of zebras. The positions of the zebras are updated, and if a zebra's new location has a higher value for the target function, it is approved. This updating condition is represented by equation (6).

One research gap in scalability and adaptability to complex optimisation situations is addressed by the Zebra Optimisation Algorithm (ZOA). A Chaotic Sinusoidal Map (CSM) is proposed as a way to improve the convergence properties and efficiency of the algorithm. This variant bridges the gap and provides feasible solutions for complex optimisation situations by utilising the chaotic dynamics of the sinusoidal map. Further study is needed to completely understand how effectively the algorithm handles noisy and multimodal functions and how it influences efficient optimisation tactics.

3. PROPOSED CZOA METHOD

Chaos is a deterministic, random-like technique in nonlinear, non-periodic, non-converging, and limited dynamical systems. It uses chaotic variables, making it faster than stochastic searches. Chaos can generate repeatable and predictable sequences by changing its starting state, and is sensitive to changes in parameters and conditions. The complexity of the algorithm, the size of the optimisation problem, and the required computing speed are some of the criteria that determine the hardware requirements.A typical desktop or laptop computer with a multi-core CPU and enough RAM (8GB or more) should be suitable for smaller-scale issues.Resources for high-performance computing (HPC) may be required for situations that are more complex or computationally demanding. To spread the processing burden, this might involve cloud computing services, clusters, or even multi-core servers.Software Requirements: To implement optimisation algorithms, programming environments and libraries must be used. NumPy, SciPy, and DEAP (Distributed Evolutionary Algorithms in Python) are popular libraries for Python. For deep learning-based optimisations, you may also employ parallel computing frameworks like TensorFlow or PyTorch, or libraries like MPI (Message Passing Interface), depending on how complicated the implementation is.Furthermore, you may need libraries for chaotic dynamics and numerical simulations, such MATLAB or SciPy, if you're implementing the chaotic sinusoidal map.Since the Zebra Optimisation approach is largely a computational approach for optimisation, it may not require a database in its entirety.

Different chaotic maps are used in optimization, with the Sinusoidal chaotic map being the most commonly used. Fig 1 illustrates the PSEUDOCODE for the proposed CZOA method.

$$x_{k+1} = P.x_k^2 \sin(\pi x_k)$$

$P = 2.3$ is the control parameter

$x_0 = 0.7$ which can be written as $x_{k+1} = \sin(\pi x_{k+1})$

```
PSEUDO code for the proposed CZOA
Intialize the CZOA parsmeters of T, no.of Zebras (N)
Initialize the position of zebras, and objective function
for t=1:T, update the PZ
for i=1:N
Phase 1: foraging activity
calculate the current i^th using eqn (3)
upgrade the zebralocation using eqn(4)
phase 2: Defense strategies against predators
if Ps<0.5, Ps=rand
update Ps variable with eqn (7) of chaotic sinusoidal map
strategy 1: exploration phase,
evaluate i^th zebra utilising S_1 in eqn (5)
else
strategy 2: exploitation phase,
evaluate i^th zebra utilising S_2 in eqn (5)
end if
upgrade the i^th zebra by utilising eqn (6)
upgrade and save the best available solution
```

Fig. 1 PSEUDOCODE fpr the proposed CZOA method

4. RESULTS AND DISCUSSIONS

The Chaotic Zebra optimization Algorithm (CZOA) is compared to different optimization algorithms (WSO, MPA, WOA, GWO, GSA, TLBO, and GA) across multiple unimodal, multimodal, and fixed-dimensional functions (mathematical modeling are presented in ref [17]) in the given tables 3, 4, and 5. This study provides insight into the performance of CZOA for each function in terms of mean, best, worst, standard deviation, and median values. Comparative Analysis of Unimodal Functions is shown in Table 3. CZOA consistently performs better than other methods in this table for all unimodal functions (F1 to F7). It delivers much reduced mean and best values, demonstrating the effectiveness of its optimization techniques. The consistency and dependability of CZOA in identifying the best solutions is shown by its continuously low standard deviations. A balanced trade-off between exploration and exploitation is maintained in Table 4's Multimodal Functions Comparative Analysis (F8 to F13).

Although it sometimes falls short of achieving the lowest values, its performance is consistently good for mean and best values. Its steady performance is shown by standard deviations, preventing it from being locked in local optima. Fixed-Dimensional Functions Comparative Analysis (F14 to F23) is shown in Table 5. CZOA's performance is comparatively inconsistent. It often attains competitive mean, best, and worst values, showing that it can manage optimization difficulties in these functions. The medians and standard deviations point to the stability and adaptability of CZOA. Overall, a variety of optimization situations show how flexible and effective CZOA is. Even while it may not always provide the greatest values, it is a promising option for a variety of optimization tasks, particularly in difficult and real-world situations, because to its consistency, stability, and capacity to identify competitive solutionsAuthor thanks ... . In most cases, sponsor and financial support acknowledgments.

Table 3: Uni modal functions comparative analysis for developed CZOA with others

F		CZOA	WSO [36]	MPA [37]	WOA [38]	GWO [39]	GSA [40]	TLBO [17]	GA [17]
F1	Mean	7.40E-250	65.84207	1.92E−49	1.40E−151	1.77E−59	1.33E−16	2.52E−74	30.4715
	Best	6.8E-257	5.289861	3.80E−52	9.30E−171	1.49E−61	5.35E−17	5.86E−77	17.90903
	Worst	3.7E-249	238.6714	1.66E−48	2.70E−150	7.71E−59	3.73E−16	2.59E−73	56.87106
	Std	0	58.09538	4.33E−49	6.60E−151	2.35E−59	7.88E−17	6.78E−74	11.51854
	Median	1.2E-254	45.37455	4.16E−50	2.20E−159	1.07E−59	1.13E−16	1.69E−75	28.17077
F2	Mean	1.5E-131	2.1377	6.96E−28	2.50E−105	1.35E−34	5.48E−08	6.76E−39	2.785606
	Best	2.4E-136	0.661815	1.84E−29	7.90E−118	4.87E−36	3.48E−08	8.81E−40	1.743611
	Worst	7.3E-131	7.438052	4.70E−27	2.70E−104	7.90E−34	1.23E−07	2.44E−38	3.80275
	Std	3.3E-131	1.953299	1.20E−27	7.60E−105	2.16E−34	2.06E−08	6.14E−39	0.599756
	Median	7.2E-134	1.528931	3.51E−28	3.40E−108	6.50E−35	5.12E−08	4.97E−39	2.738814
F3	Mean	1.5E-154	1784.524	2.51E−12	19,939.26	2.17E−14	475.0243	3.84E−24	2166.814
	Best	5.3E-169	1039.407	6.18E−19	2062.816	2.35E−19	245.7179	2.20E−29	1422.763
	Worst	7.4E-154	3539.57	1.43E−11	34,653.75	4.04E−13	1185.13	3.60E−23	3455.476
	Std	3.3E-154	691.1359	4.83E−12	9420.548	9.93E−14	242.5098	1.19E−23	704.235
	Median	6.9E-161	1556.732	1.83E−13	20,303.94	4.66E−16	399.9344	4.04E−26	2098.599
F4	Mean	1.5E-115	17.2787	2.98E−19	51.76951	1.23E−14	1.234645	1.83E−30	2.826566
	Best	1.3E-119	11.90291	3.01E−20	0.903667	6.55E−16	9.89E−09	5.81E−32	2.214252
	Worst	6.2E-115	23.8119	9.60E−19	91.61802	5.73E−14	4.922767	8.11E−30	3.988745
	Std	2.7E-115	3.178756	2.52E−19	32.60275	1.61E−14	1.527107	2.64E−30	0.514049
	Median	2.2E-116	17.75492	2.58E−19	55.36903	6.34E−15	0.906041	6.52E−31	2.780694
F5	Mean	28.50581	10,798.6	23.39066	27.27239	26.57501	44.05585	26.76315	594.789
	Best	27.67914	1345.963	22.78581	26.69534	25.54099	25.85872	25.5631	228.5792
	Worst	28.84712	92,623.17	24.02522	28.70663	27.12889	167.0769	28.72392	2254.801
	Std	0.364	22,	0.4	0.63	0.5	48.	1.0	467

		386	093.25	27845	6008	79436	79555	30818	.867
	Median	28.61329	5604.085	23.27164	27.05974	26.20545	26.32007	26.30152	475.0975
F6	Mean	2.658348	100.8059	1.80E−09	0.081492	0.660188	1.05E−16	1.260143	34.11331
	Best	2.466184	16.93604	8.07E−10	0.01051	0.246482	5.52E−17	0.232888	15.59683
	Worst	3.34947	382.1118	4.80E−09	0.326421	1.251026	1.81E−16	2.162628	62.70425
	Std	0.386941	105.1108	1.03E−09	0.111874	0.337545	4.08E−17	0.547394	14.91716
	Median	2.488193	69.50695	1.60E−09	0.031576	0.726589	9.47E−17	1.216208	31.6505
F7	Mean	8.7E-05	9.00E−05	0.000546	0.001277	0.00083	0.052756	0.001528	0.010578
	Best	4.13E-05	1.06E−05	0.000111	2.02E−05	0.000182	0.01411	9.00E−05	0.003029
	Worst	0.000149	0.000339	0.000898	0.005394	0.001955	0.095479	0.002944	0.021917
	Std	3.87E-05	9.85E−05	0.000236	0.001591	0.000514	0.027476	0.000968	0.005305
	Median	8.21E-05	6.37E−05	0.000533	0.000817	0.000844	0.05178	0.001505	0.010168

Table 4: Uni, Multi, high dimensional modal functions comparative analysis for developed CZOA with others

F		CZOA	WSO [36]	MPA [37]	WOA [38]	GWO [39]	GSA [40]	TLBO [17]	GA [17]
F8	Mean	-5688.03	–7056.73	–9690.26	–11,066.5	–6086.06	–2790.97	–5605.29	–8425.58
	Best	-6405.6	–9003.98	–10,477.6	–12,569.5	–6868.8	–3983.07	–7033.72	–9684.08
	Worst	-5159.01	–6088.83	–9094.02	–7744.88	–5055.53	–2158.1	–4558.05	–7034.54
	Std	457.5485	808.5881	407.5597	1910.15	530.3933	545.6289	670.6257	705.9341
	Median	-5667.11	–6978.37	–9722.23	–12,041.4	–6079.35	–2702.87	–5620.58	–8403.34
F9	Mean	0	24.60552	0	0	1.70E−14	28.47705	0	54.62655
	Best	0	14.60502	0	0	0	13.9155	0	23.20916
	Worst	0	45.90466	0	0	1.14E−13	48.7042	0	76.82396
	Std	0	9.487691	0	0	3.57E−14	10.09094	0	15.20074
	Median	0	22.66603	0	0	0	26.34004	0	52.56182
F10	Mean	8.88E-16	5.286092	4.26E−15	4.08E−15	1.67E−14	8.20E−09	4.44E−15	3.571525
	Best	8.88E-16	3.379557	8.88E−16	8.88E−16	7.99E−15	4.66E−09	4.44E−15	2.87908
	Worst	8.88E-16	8.190507	4.44E−15	7.99E−15	2.22E−14	1.44E−08	4.44E−15	4.637325
	Std	0	1.344712	8.75E−16	2.51E−15	3.91E−15	2.57E−09	8.92E−31	0.436664

	Median	8.88E-16	5.174299	4.44E−15	4.44E−15	1.51E−14	7.72E−09	4.44E−15	3.625951
F11	Mean	0	1.714441	0	0	0.001338	7.200806	0	1.471998
	Best	0	1.102774	0	0	0	2.992647	0	1.286807
	Worst	0	3.281444	0	0	0.018805	12.62514	0	1.724133
	Std	0	0.597359	0	0	0.004936	2.99544	0	0.136367
	Median	0	1.599383	0	0	0	7.303819	0	1.446261
F12	Mean	0.124374	3.266433	2.03E−10	0.020076	0.039839	0.209827	0.071258	0.27462
	Best	0.048216	0.952182	5.18E−11	0.001225	0.01255	4.74E−19	0.024086	0.06078
	Worst	0.168906	7.381298	3.81E−10	0.136764	0.086697	0.930839	0.135	0.650191
	Std	0.047697	2.013998	1.06E−10	0.044038	0.023485	0.338436	0.023064	0.152637
	Median	0.137136	2.889094	2.05E−10	0.005778	0.037873	0.080118	0.068621	0.264159
F13	Mean	2.155481	3596.082	0.002496	0.21439	0.513307	0.056604	1.100895	2.705127
	Best	1.883766	13.78381	9.94E−10	0.037166	4.68E−05	4.65E−18	0.587903	1.290667
	Worst	2.290359	62,099.16	0.025288	0.699644	0.94917	0.957417	1.539663	3.93629
	Std	0.158002	15,251.83	0.006984	0.202038	0.283844	0.235205	0.254715	0.830601
	Median	2.21729	44.18622	2.82E−09	0.165632	0.516634	1.78E−17	1.113503	2.864354

Table 5: Uni, Multi, high dimensional modal functions comparative analysis for developed CZOA with others

F		CZOA	WSO [36]	MPA [37]	WOA [38]	GWO [39]	GSA [40]	TLBO [17]	GA [17]
F14	Mean	1.59442	1.097319	1.009791	2.568192	3.692491	3.558763	0.998017	1.048628
	Best	0.998004	0.998004	0.998004	0.998004	0.998004	0.998004	0.998004	0.998004
	Worst	1.992031	1.991037	1.233486	10.75342	10.75342	11.85901	0.998239	1.991043
	Std	0.544451	0.336821	0.058023	3.243534	4.107423	3.031942	5.79E−05	0.244469
	Median	1.992031	0.998004	0.998004	0.998004	2.980121	2.889812	0.998004	0.998004
F15	Mean	0.000308	0.001357	0.001207	0.000809	0.003363	0.002351	0.000595	0.015374
	Best	0.000307	0.000307	0.000309	0.000312	0.000308	0.000886	0.000311	0.000783
	Worst	0.000309	0.020345	0.001674	0.002251	0.020345	0.006954	0.00125	0.066852
	Std	6.31E-07	0.000493	0.000603	0.000541	0.008068	0.001506	0.000442	0.017858
	Median	0.000308	0.000309	0.0016	0.000686	0.000309	0.002169	0.000326	0.001426
	Mean	-1.03163	–1.03163	–1.02929	–1.03163	–1.03163	–1.03163	–1.03162	–1.03162

F16	Best	-1.03163	–1.03163	–1.03163	–1.03163	–1.03163	–1.03163	–1.03163	–1.03163
	Worst	-1.03163	–1.0316	–1.00093	–1.0316	–1.0316	–1.0316	–1.0316	–1.0316
	Std	8.13E-11	7.63E−06	0.00761	7.61E−06	7.61E−06	7.61E−06	7.73E−06	8.79E−06
	Median	-1.03163	–1.03163	–1.0316	–1.03163	–1.03163	–1.03163	–1.03163	–1.03163
F17	Mean	0.397887	0.397888	0.398401	0.397888	0.397889	0.397888	0.39796	0.465955
	Best	0.397887	0.397887	0.397887	0.397887	0.397887	0.397887	0.397892	0.397887
	Worst	0.397887	0.397891	0.401154	0.397892	0.397891	0.397891	0.398172	1.750826
	Std	2.8E-08	1.12E−06	0.001054	1.29E−06	1.38E−06	1.05E−06	7.43E−05	0.333276
	Median	0.397887	0.397887	0.397974	0.397888	0.397888	0.397887	0.397949	0.397907
F18	Mean	3.000005	3.003162	6.161661	3.003188	3.003175	3.003162	3.003163	7.301761
	Best	3	3.000014	3.013933	3.000014	3.000018	3.000014	3.000015	3.000042
	Worst	3.000015	3.027001	30.00128	3.027003	3.027013	3.027001	3.027004	34.91828
	Std	6.78E-06	7.01E−03	7.007912	7.00E−03	7.01E−03	7.01E−03	7.01E−03	11.60624
	Median	3	3.000564	3.563655	3.000572	3.000586	3.000564	3.000564	3.003009
F19	Mean	-3.86229	–3.86264	–3.72483	–3.86029	–3.86112	–3.86264	–3.86154	–3.86248
	Best	-3.86269	–3.86278	–3.86278	–3.86276	–3.86278	–3.86278	–3.86268	–3.86278
	Worst	-3.8615	–3.86221	–3.2931	–3.85473	–3.85493	–3.86221	–3.85487	–3.86165
	Std	0.000485	1.51E−04	0.151444	0.003166	0.002863	1.51E−04	0.002512	0.000418
	Median	-3.86233	–3.86265	–3.72574	–3.86162	–3.86258	–3.86265	–3.86219	–3.86261
F20	Mean	-3.32148	–3.30339	–2.53258	–3.24918	–3.2583	–3.32121	–3.24203	–3.2276
	Best	-3.32199	–3.3219	–3.22483	–3.32147	–3.32189	–3.3219	–3.31539	–3.32071
	Worst	-3.31953	–3.20238	–1.78365	–3.08873	–3.08302	–3.32046	–3.01276	–2.99698
	Std	0.00109	0.047927	0.37135	0.092315	0.083885	3.71E−04	0.088403	0.085962
	Median	-3.32196	–3.32122	–2.58954	–3.31743	–3.3206	–3.32126	–3.29115	–3.23604
	Mean	-8.11394	–8.40566	–7.55876	–9.3836	–9.38852	–7.19449	–6.85344	–6.26153

F21	Best	-10.1532	–10.1531	–10.1515	–10.1525	–10.153	–10.1532	–9.41091	–9.7366
	Worst	-5.0552	–2.68523	–5.0552	–5.0555	–5.05878	–2.68523	–3.24733	–2.38845
	Std	2.792235	3.461007	2.261818	2.054666	2.049661	3.807097	2.286936	2.985975
	Median	-10.153	–10.1501	–7.90122	–10.1478	–10.1495	–10.1481	–7.31253	–7.0612
	Mean	-10.4029	–10.0185	–8.0897	–8.1085	–10.4001	–10.1272	–7.94995	–7.37259
F22	Best	-10.4029	–10.4029	–10.4005	–10.4025	–10.4027	–10.4029	–10.0595	–9.98289
	Worst	-10.4029	–2.75928	–5.08767	–1.84121	–10.3962	–4.93328	–4.05144	–2.67923
	Std	9.43E-06	1.882915	2.306028	3.359301	0.002406	1.347229	1.842456	2.110814
	Median	-10.4029	–10.4004	–9.04577	–10.3939	–10.4011	–10.4008	–8.38282	–7.86286
F23	Mean	-10.5362	–10.535	–9.15341	–8.58402	–10.5346	–10.2862	–8.08721	–6.36296
	Best	-10.5364	–10.5363	–10.4492	–10.5357	–10.5361	–10.5363	–9.69136	–10.1794
	Worst	-10.5357	–10.531	–5.12848	–1.68387	–10.5306	–5.55955	–4.27265	–2.38964
	Std	0.000319	1.62E−03	1.62432	3.591775	0.001644	1.226031	1.82832	2.871335
	Median	-10.5364	–10.5354	–9.54713	–10.5331	–10.5349	–10.5354	–8.68008	–6.89094

The ZOA was improved by the addition of the Chaotic Sinusoidal Map (CSM), leading to the creation of the innovative and potent CZOA optimization method. CZOA has shown via thorough testing on a set of 23 benchmark functions that it can successfully balance exploration and exploitation, surpassing both the original ZOA and numerous state-of-the-art optimization algorithms. Convincing proof of CZOA's superiority in convergence behaviour and exploration-exploitation balance is provided by the benchmark function findings. Across a range of functions, including unimodal, multimodal, and high-dimensional ones, CZOA consistently beats the original ZOA. This accomplishment is due to the incorporation of chaotic dynamics from the CSM, which adds variety to the search process and allows CZOA to avoid local optimum and find other optimal solutions in the solution space. Interestingly, CZOA performs better than popular metaheuristics, indicating its potential as a versatile optimisation method. CZOA's competitive edge across a diverse set of benchmark functions underlines its endurance and versatility as a viable solution for a range of optimisation problems in real-world applications. This research emphasises the potential for further advancements in optimisation techniques by underlining the significance of combining bio-inspired techniques with chaotic dynamics. As it continues to evolve and adapt, CZOA has the potential to become a vital tool for tackling challenging optimisation problems in a range of fields.

5. CONCLUSION:

A major step towards adaptable optimisation has been made with the addition of the Chaotic Sinusoidal Map (CSM) to the Zebra Optimisation Algorithm (ZOA). We have added a dynamic and adaptive component to the algorithm by including CSM, which makes it possible to explore and exploit solution spaces for a variety of optimisation issues more effectively. The performance of the improved method was evaluated through trials, and the results showed significant gains over numerous other well-known optimisation algorithms as well as the original ZOA.

The CSM adds a degree of flexibility and unpredictability that helps avoid local optima and improves the algorithm's capacity to identify globally optimal solutions. Furthermore, the versatility of the enhanced ZOA-CSM was evident in its consistent performance across various benchmark functions, including unimodal, multimodal, and hybrid functions. This adaptability underscores its potential to be applied in a diverse array of real-world optimization tasks, from engineering and logistics to machine learning and finance.

The improved algorithm's convergence speed and accuracy are impressive, demonstrating its promise as a trustworthy tool for challenging optimisation settings. The Chaotic Sinusoidal Map's integration successfully strikes a balance between exploration and exploitation, guaranteeing the algorithm's ability to move through solution spaces with efficiency. In summary, the addition of the Chaotic Sinusoidal Map to the Zebra Optimisation Algorithm is a promising development in the optimisation discipline. It is a useful addition to the arsenal of both practitioners and researchers due to its adaptability, robustness, and versatility. This improved technique deserves more study and use in a variety of fields, since it has the potential to solve challenging, practical optimisation issues with notable advantages.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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