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Human Learning-Based Cognitive Elephant Herding Optimization Technique

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Abstract:

The Cognitive Elephant Herding Optimization (CEHO) technique, a new variation of Elephant Herding Optimization (EHO) that incorporates human learning principles-based techniques, has been proposed in this study. Two novel strategies—Socially Interactive Guidance (SIG) and Self-Adaptive Parameterized Perception (SAPP)—have been developed as a result of incorporating these concepts into EHO. The SIG approach incorporates guidance-based learning as its inspiration for the exploration phase. Similar to this, SAPP techniques are devoted to the exploitation phase that incorporates Self-Regulating Perception (SRP) and Generation Gap (GG) cognitive skills from people into the technique. On the CEC 2013 benchmark suits, a significant number of experimental assessments have been carried out to evaluate the significance of the proposed strategy. Moreover, the algorithm is compared to some of the state-to-art algorithms, namely elephant herding optimization (EHO), differential evolution (DE), sine cosine algorithm (SCA), and whale optimization algorithm (WOA), in order to validate the proposed performance and convergence of CEHO against selected functions of CEC 2013 benchmark suits.

Keywords: *Cognitive based, Elephant Herding Optimization, Learning methodology, Self and Social Learning.*

I. INTRODUCTION

As it is impossible to find a perfect solution to real-time problems due to their complexity, optimization has become more and more popular among researchers. Due to the complexity of issues like the Unequal Area Facility Layout Problem (UA-FLP) [1], the research community has turned its focus toward evolutionary computation because the traditional deterministic algorithms among them have been unable to produce outcomes that are optimum. The naive-inspired metaheuristic algorithms have established themselves as superior optimizers in the family of evolutionary computation [2]. The Elephant Herding Optimization (EHO) algorithm [3] is one such method that was recently introduced and was inspired by the herding behavior of elephants. In a very short span of time, this algorithm grabbed the attention of many researchers who have utilized it for solving complex real problems and found optimum solutions [4,5]. Nevertheless, in some cases, it did not perform well as compared to other state of the art algorithms [6] that promoted the researchers to apply fine tuning of its parameters. Also, performance enhancement can be cooperated with human learning-based principles which is getting hype and emerging a better performance enhancement tool for the nature-inspired algorithms that result in better optimum solutions [7,8] whose further details are enclosed in the next section. The rest of the paper is organized into VI sections. Section II describes briefly the background of the study, Section III is about the problem statement and its proposed solution. Section IV is about methodology and also proposes modifications in the light of human learning strategies as details of CEHO and Section V presents the experimental setup, and setting of parameters. Section VI represents the results and discussions. Finally, Section VII concludes the whole study.

II. LITERATURE REVIEW

EHO has rapidly grown in popularity and has been successfully applied to a variety of real-world issues, including the optimal power flow problem [4] and home energy management systems [5], where it has successfully and efficiently offered optimized solutions with a quicker convergence rate. In light of the algorithm's massive popularity, it applies to find out optimum solutions for many complex real world problems but in a few of them, it did not perform well [6] that led the further attention towards fine tuning of the algorithm so studies have been done to examine how EHO algorithm might be modified to reduce their shortcomings and enhance its performance. Recently, a modified EHO algorithm (MEHO) has proposed and brought changes in its configuration that is the influence of the fittest elephant has been used to update the middle-positioned elephants of the clans [6]. Also, the enhanced elephant herding optimization method (EEHO), which involves updating and modification in clan updating operations, was recently proposed. Apart from updating the parameters of the EHO algorithm, another technique is the hybridization of different evolutionary algorithms to EHO. L. Goel utilized hybrid EHO in recognizing the English characters affected by external noise distortion [9]. Robots are now widely used in the integration of IOT to cope with human-related dependencies so an improved EHO is applied for the path planning of Robots [10]. Also, enhancement in EHO has been utilized in Association rule hiding techniques for solving various real-life problems [11]. Hybridization of convolutional neural networks with EHO effectively results in the prediction of heart disease [12]. Moreover, the efficiency of routing protocol and clustering for wireless sensor networks [13] and mining of utility item sets [14] has been enhanced by using improved EHO. It has been noted that the algorithm’s alteration has either increased its convergence rate or accelerated its convergence to optimal outcomes. It has been noted that the algorithm’s alteration has either increased its convergence rate or accelerated its convergence to optimal outcomes.

Researchers are still in demand of getting an EHO algorithm that can deliver better-optimized solutions with a faster convergence rate. Swarm-based evolutionary algorithms have recently embraced learning methodologies based on human learning principles [7]. According to it, human beings are better planners and learn more effectively [8]. Human learning concepts have been applied to many optimization algorithms, such as self-adaptive differential evolution (SADE) [9], feature subset selection using DE [10], etc., and the algorithms have significantly improved in terms of performance. To the best of our knowledge, relatively little effort has been made to improve the performance of the EHO algorithm. Additionally, it has been noted that the approach performs less well when attempting to resolve challenging real-world optimization issues, such as the multi-objective distributed energy resource (DER) accommodation problem [6]. Our study suggests that the algorithm needs its parameters fine-tuned in order to perform equally well on complex problems [11], as Parametric tuning improves the performance of evolutionary algorithms. But, no human learning techniques have been incorporated into the EHO algorithm to improve its convergence rate which is the motivation of our work. To investigate further, the behavior of the EHO algorithm is investigated using the theory of human learning, and a new technique known as Cognitive Elephant Herding Optimization (CEHO) is presented. The suggested technique uses a Self-Adaptive Parameterized Perception (SAPP) approach to the parameter of clan update phenomena and a Socially Interactive Guidance (SIG) strategy for elephant clan-separation behavior. The proposed strategies have been tested in twenty-seven distinct settings for CEHO, and all of them have been examined using the benchmark functions from CEC 2013 [12]. The Bonferroni-Dunn test is then used to statistically evaluate the performance [13]. The experimental findings of the CEHO technique show that applying human learning can enhance CEHO's performance.

III. PROBLEM STATEMENT AND ITS PROPOSED SOLUTION

It has been observed that the algorithm's modification has sped up or improved the rate at which it converges to the best results. Researchers continue to be in need of an EHO algorithm that can produce more rapid convergence and better-optimized solutions. Recently, learning approaches grounded in human learning principles have been accepted by swarm-based evolutionary algorithms [7]. To the best of our knowledge, not much has been done to enhance the EHO algorithm's performance. Furthermore, it has been shown that the method does not perform as well when try-ing to address difficult real-world optimization problems, like the multi-objective distributed energy resource (DER) accommodation problem [6]. According to our research, the algorithm requires parameter tweaking to function as effectively as it does on complicated issues [11], since parametric tuning enhances the efficiency of evolutionary algorithms. However, our work is motivated by the fact that no human learning techniques have been applied to the EHO algorithm to increase its convergence rate.

IV. METHODOLOGIES AND TECHNIQUES

A. Optimization Phenomenon Of The Eho Algorithm

In the EHO algorithm, the natural social guidance of elephant species has been adopted comprising of clan updat-ing operator and clan separating operator. The clan updating operator incorporates the updating of new positions for the leader and other elephants in the clan and is modeled in eqs. (1) to (3). The separating of the clan is referred to as the replacing of the worst elephant with the randomized selection in order to fill up the clans modelled as equation 4 [14].

$$x_{new,ci,j} = x_{ci,j} + \alpha * (x_{best,ci} - x_{ci,j}) * r \quad \text{---------------} \quad (1)$$

$$X_{new,ci,j} = \beta * X_{center,ci} \quad \text{--------------------} \quad (2)$$

$$Xcenter, ci, d = {}^{1}\!/_{nci} * \left(\sum_{j=1}^{nci}(Xci, j, d)\right) \quad \text{------------------------} \quad (3)$$

$$x_{worst,ci} = x_{min} + (x_{max} - x_{min} + 1) * rand \quad \text{----------------} \quad (4)$$

where, α ϵ [0, 1] and r ϵ [0, 1] and Xbest, ci represents the fittest Matriarch in a clan ci and “α” involves in the positioning of elephants other than Matriarch. Here “d” shows the particular dimension, β ϵ [0, 1] is the influencing factor on the position of the Matriarch. Xmin and Xmax are the lower upper bound of the elephant's individual position and Xworst, ci is the male elephant to be separated from clans.

Further, the updating phase of a Matriarch in a clan was presented as the sum of the best solution of each clan summed up with β multiplied by the mean position of the elephant, mathematically presented in equation 5. Moreover, it was further highlighted that young and weak elephants should be kept near the stronger female elephants in order to save them from predators modelled as equation 6. The parametric study of α and β were also the main themes of the study. The settings were proposed as fixed values of α = 0.8 and β = 0.1 through the trial and error method [2].

$$Ynew,cj,i = Ybest,cj,i + \beta * Ycenter,cj \quad \text{-------------------} \quad (5)$$

$$Yworst,cj,i = Yfitness,c,j \quad \text{-------------------------} \quad (6)$$

where, Ynew, cj,i is the new candidate in the clan, Ybest, cj,i is the best candidate, and Ycenter,cj is the candidate placed at the center position. Also Yworst, cj,i is the worst candidate and Yfitness,c,j is the most fittest candidate. Inspired by these findings, this paper explores α and β tuning methodologies to fasten its convergence rate towards optimized solutions.

B. Cognitive Elephant Herding Optimization (Ceho) Technique

Relating to human learning psychology, in this research, two strategies referred to as Socially Interactive Guidance (SIG) and Self-Adaptive Parameterized Perception (SAPP) have been introduced for the basic EHO algorithm. Incorporating the proposed modifications, a new variant of the EHO algorithm has been developed referred to as the Cognitive Elephant Herding Optimization (CEHO). The details of the strategies and their combined effect on the CEHO are presented next.

Clan Separating through Socially Interactive Guidance (SIG) Strategy: The phenomenon of social contact among people serves as the driving force behind the SIG approach. Humans learn via engaging in social interactions, and they get cognitive guidance from their environment accordingly. In order to provide a better method for the clan-separating operator, the EHO algorithm incorporates this spectacle of human social interaction. This is accomplished by combining an elitism strategy for clan separation with directionally driven guidance. By adopting the SIG technique, it has been suggested that the mean position of best candidates from various clans will be chosen to replace the weakest candidate, also known as the male elephant. In this study, three different settings have been proposed i) mean position of top four referred to as the Quad strategy ii) mean position of top five referred to as the Pentagon strategy and iii) mean position of top six referred to as the Hexagon strategy. In the Quad strategy, it has been proposed that for every clan, the worst candidate is replaced by collaborating with the best candidates of the top four clans which may not have equal distance from each other. This inspiration is taken from weak performers' cognition as they seek guidance from others. The strategy is illustrated in Figure 1.

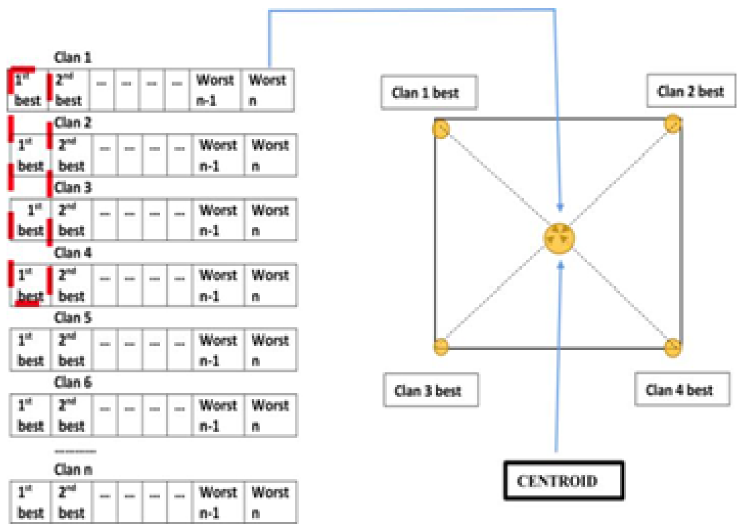

Figure 1: Quad strategy

Similarly, in the Pentagon strategy, the worst candidate in every clan is replaced by collaborating with the best candidates of the top five clans as illustrated in Figure 2.
Finally, in the Hexagon strategy, the worst candidate in every clan is replaced by collaborating with the best candidates of the top six clans as elaborated in Figure 3.
The positions of every individual elephant is updated for each population for this, Self-Adaptive Parameterized Perception (SAPP) strategies have been proposed as presented in the next section.

Self-Adaptive Parameterized Perception (SAPP) Strategies for Clan Updating Phenomenon: Human Learning theories suggested SAPP techniques for updating the placements of each individual elephant and the clan leader, which resulted in a higher rate of convergence. A person with strong cognitive abilities and profound insight becomes a group leader and mentors others in terms of human psychology [15]. This inspired the development of the Self-Regulating Perception (SRP) and Generation Gap (GG) methods, two divergences that illustrate the clan update phenomenon using the principles of human learning.

Self-Regulating Perception (SRP): Self-Regulating Perception (SRP) is a component of SAPP techniques that suggested the Matriarch's (the clan's leader) updating method. The leader is treated with exceptional importance and high respect in the human psychology show. Inspired from this, in the EHO algorithm, according to the proposed strategy, every leader should have their own perspective importance so, SRP deals with the positional updating of a Matriarch where β has been proposed to be gradually changed either by randomized distribution or can be calculated by dividing it into the small division as modelled in equations 7 and 8,

$$\beta new = rand(\beta max, \beta min) \text{ ------------ } (7)$$
$$\beta new = \beta i - ((\beta max - \beta min)/\lambda) \text{ -----------}(8)$$

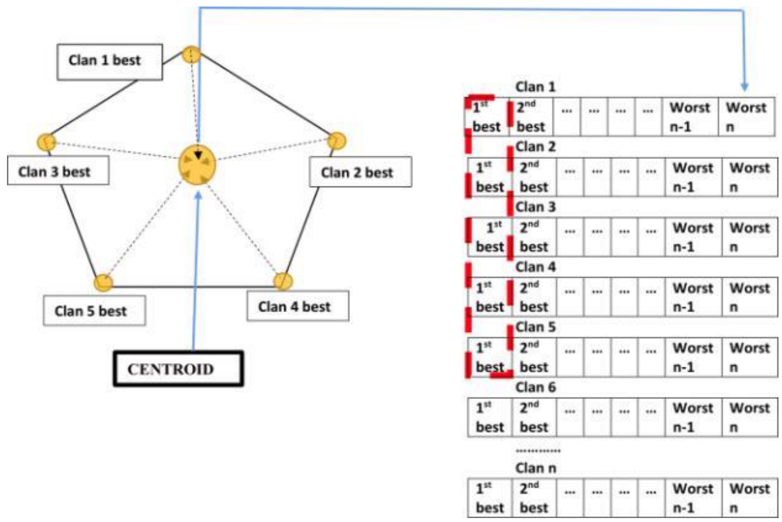

Figure 2: Pentagon Strategy

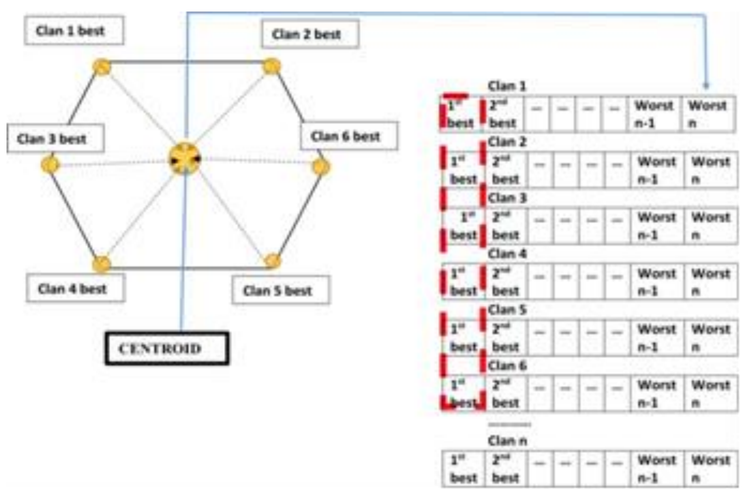

Figure 3: Hexagon strategy

where βmax is 0.2, βmin is 0.01 and βi is the iteratively calculated value of β ϵ [0.2, 0.01]. The value λ is chosen to either 10 or 20 for the selection of β values for the best of each clan as linearly decreasing from 0.2 to 0.01 for λ = 10

(Ld1) and 0.2 to 0.1 for λ= 20 (Ld2). The impact of these settings of β are studied later in section 4.2. The SRP of the values of β for the leaders residing in different clans can be visualized in Figure 4 for equation 7 and in Figures 5 and Figure 6 for (Ld1) and (Ld2) respectively.

Next, a Generation Gap (GG) strategy has been proposed for updating the position of elephants other than the leader.

Generation Gap (GG) Strategy: It has been indicated in human learning psychology [16], that as time passes every generation is smarter than their previous generation. It creates a generation gap not only in the physical aspect but also in their cognitive skills according to every individual's mind. Inspired by this, it has been proposed that when updating is shifted from one generation to another there should be a slight difference in the attributes. This strategy depends upon a parameter α for obtaining new positions of elephants other than Matriarch. Moreover, it is duly suggested that the α parameter of the basic EHO algorithm should not be increased for the entire duration as it will become too large and bring slower convergence to the algorithm. Therefore, it is proposed that α to be gradually increased up to 50% of the iterations and would remain constant for the rest of the iterations for the CEHO technique as illustrated in Figure 7.

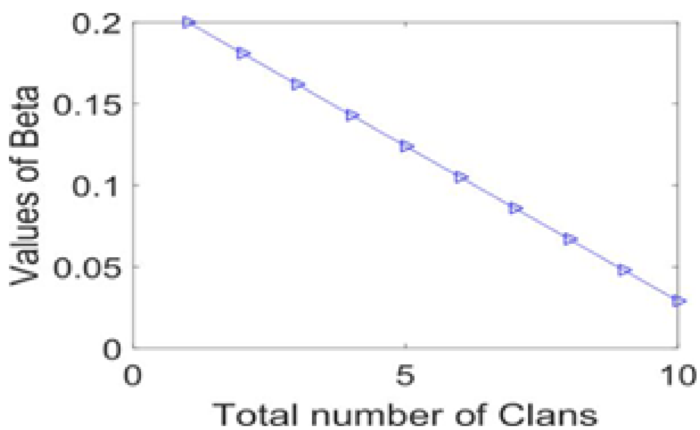

Figure 4: Graphical Representation of β Selection in one iteration

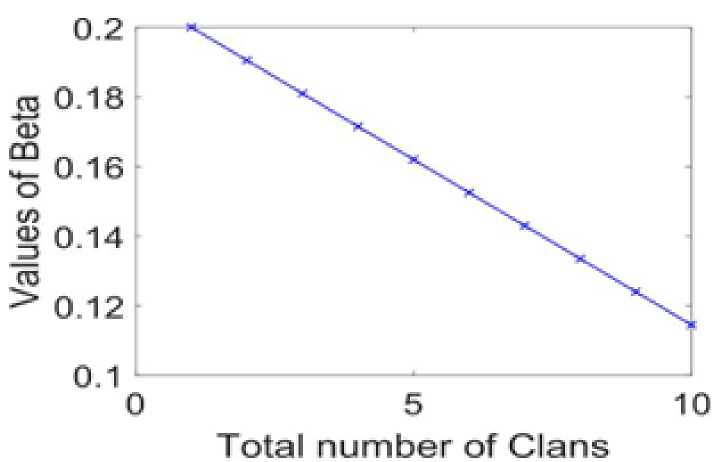

Figure 5: Graphical Representation of β Selection for (Ld1) in one iteration

This proportional increase in the value of parameter α is expressed mathematically in the following: where, α˙ is an initial value of α, αh is the higher bound of α= 1.2 and αl is the lower bound of α = 0.01 and Nmax is the total generation count. In this research three different initial values of α˙ are initially proposed as 0.785, 0.895 and 0.985 and the best among them has been chosen through experimental evaluation as presented later in the section of Selection of Parameters. Hence, α will be generated as α ϵ [1.6-0.5].

V. PERFORMANCE EVALUATION

This section provides a systematic performance evaluation of the Cognitive Elephant Herding Optimization (CEHO) technique. This section includes experimental setup, selection of parameters, and experimental results.

A. Experimental Setup

In order to validate the proposed strategies, standardized benchmark functions from CEC 2013 [17] test suites have been used. The running experimental evaluations are performed using MATLAB R2018a software on Intel ®Core TM i-5 @ 2.8GHz, a hardware system having 4.00 GB RAM, Windows 10 Professional. First, to analyze the effect:

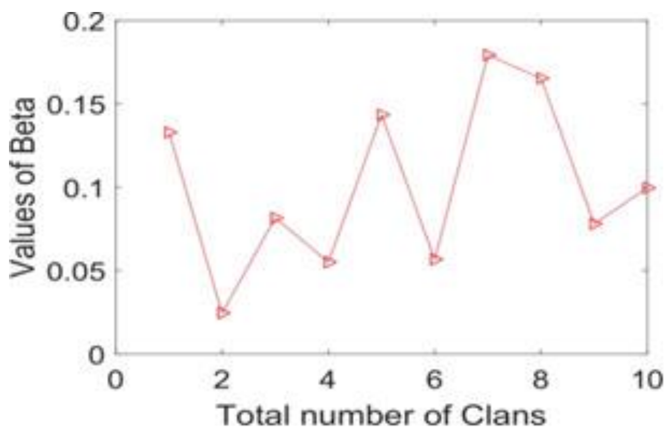

Figure 6: Graphical Representation of β Selection for (Ld2) in one iteration

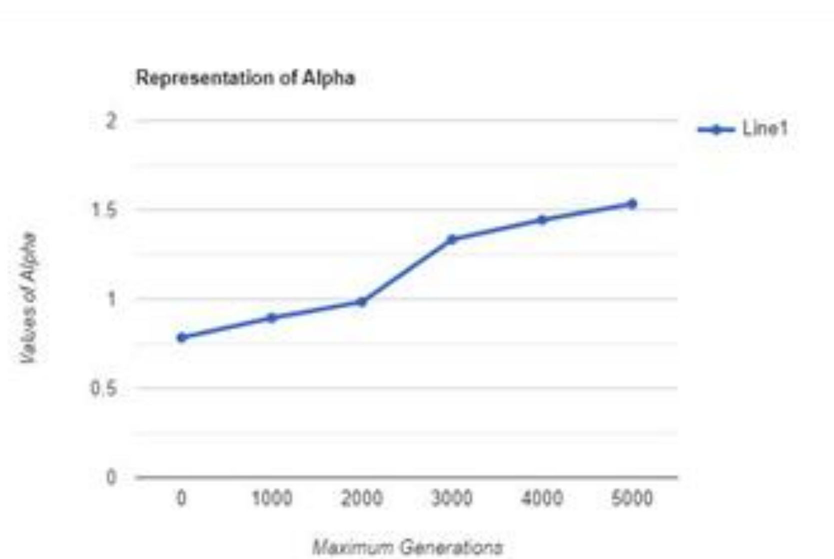

Figure 7: Graphical Representation of α Selection

of the proposed strategies and to choose the best among them the 9 benchmark functions consisting of 3 uni-modal, 3 multimodal, and 3 hybrid functions of CEC 2013 have been utilized. The maximum generation is set to 5000 evaluated on 30 dimensional problems with a population size of 100 candidates divided into 10 clans. Furthermore, the clan update operators α and β and the clan separation strategies have been modified and several different possibilities for each operator have been proposed in this study. An extensive experimental evaluation has been performed on all the possible combinations of the proposed setting, to choose the best possible combinations. The analysis is presented next.

B. Selection Of Parameters

In previous studies available in the literature, the values of α are either fixed [2, 11] or linearly increased with the generations [18]. Instead, in this study, α has been initialized with three different values 0.985, 0.895, and 0.785 introducing three variants of α which will gradually increase up to 50 percent of total generations to a maximum value of 1.3348, 1.4448, 1.5348. Similarly, three different settings of β are proposed in equations 8 and 9 and Section II as random selection, linearly decreasing in the range 0.2—0.01 (Ld1) and linearly decreasing in the range 0.2—0.1 (Ld2). Finally, three different clan separation strategies viz.; Quad, Pentagon, and Hexagon are proposed. In order, to select the best strategy, a set of possible combinations of strategies have been organized as shown in Table 1.

Table 1: Set of all Strategies Parametric settings

GGS	SRP	SIG	Str. #	GGS	SRP	SIG
α = 0.895	β = (Ld2)	Q	15	α = 0.785	β= random	P
α = 0.895	β = (Ld1)	Q	16	α = 0.985	β = (Ld2)	P
α = 0.895	β=random	Q	17	α = 0.985	β = (Ld1)	P
α = 0.785	β = (Ld2)	Q	18	α = 0.985	β= random	P
α = 0.785	β = (Ld1)	Q	19	α = 0.895	β = (Ld2)	H
α = 0.785	β= random	Q	20	α = 0.895	β = (Ld1)	H
α = 0.985	β = (Ld2)	Q	21	α = 0.895	β= random	H
α = 0.985	β = (Ld1)	Q	22	α = 0.785	β = (Ld2)	H
α = 0.985	β= random	Q	23	α = 0.785	β = (Ld1)	H
α = 0.895	β = (Ld2)	P	24	α = 0.785	β= random	H
α = 0.895	β = (Ld1)	P	25	α = 0.985	β = (Ld2)	H
α = 0.895	β= random	P	26	α = 0.985	β = (Ld1)	H
α = 0.785	β = (Ld2)	P	27	α = 0.985	β= random	H
α = 0.785	β = (Ld1)	P				

Here Q is for the Quad strategy, P is for the Pentagon strategy and H is for the Hexagon strategy, GGS is for the Generation Gap Strategy, SRP is for Self-Regulating Perception, SIG is for the Socially Interactive Guidance strategy. Furthermore, to identify the most feasible strategy for enhancing the performance of the proposed technique, the different combinations of strategies are tested on nine functions from CEC 2013 which includes 3 unimodal, 3 multi-modal and 3 hybrid functions. Their experimental mean error results were then presented in the form of pictorial histograms to visualize their performance. All the settings have been kept the same as described in Section II and twenty-five runs were performed. The mean error results (F(x)-F(x*)) have been recorded for all combinations and are presented as histograms [19] in Figure 8, Figure 9, and Figure 10.

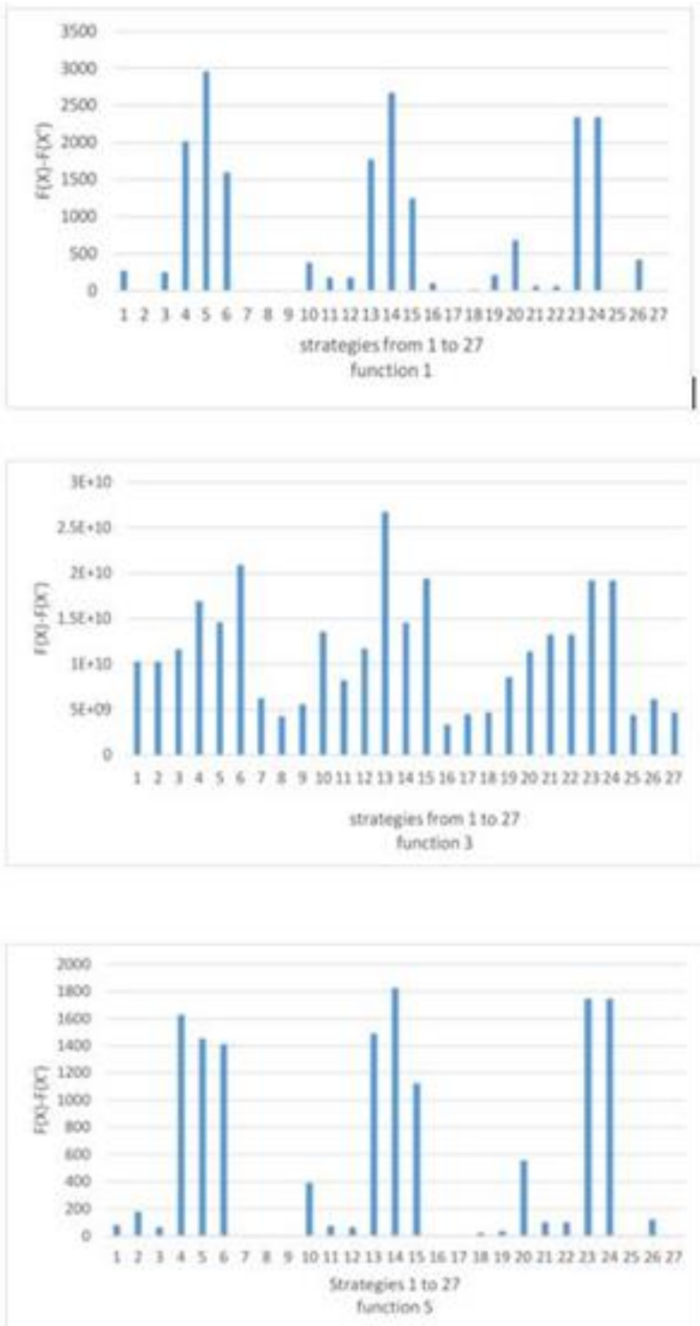

Figure 8: Histograms of all possible strategic settings on functions F1, F3 and F5 of CEC 2013
Source: Authors' Estimation

Figures 8a, 8b and 8c show the performance for functions 3, 5 and 7 respectively. Similarly, Figures 9a, 9b and 9 provide the performance for functions 13, 16 and 20. Finally, Figure 10 provides the performance for strategies for functions 24, 25, and 28. It is evident from the results that overall performance for strategies 10-18 i.e. Pentagon in SIG did not perform well in most of the multimodal and hybrid functions as it did not provide uniform guidance to the weaker candidates in the Socially Interactive Guidance strategy, whereas Quad and Hexagon performed better than Penta-gon as it provided with uniformly distributed guidance to the weaker candidate which enhanced their performance in most of the benchmark functions of CEC 2013. Therefore, the Pentagon could not be further utilized in the settings of the proposed technique. Whereas, the other strategies are performing closer to each other. Hence, to perform a comparative analysis, for observing the significance of the proposed strategies over each other Friedman's test [17] followed by the Bonferroni-Dunn test [13] has been performed.

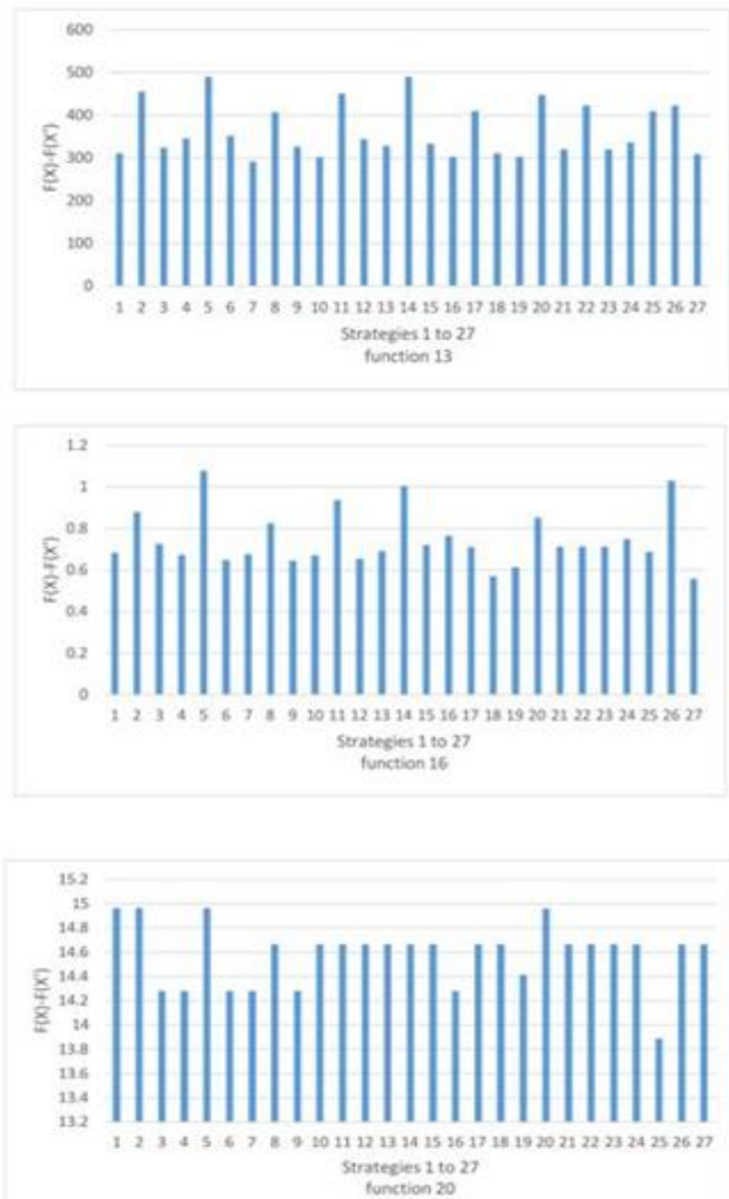

Figure 9: Histograms of all possible strategic settings on functions F13, F16 and F20 of CEC 2013

Friedman's test has been utilized to verify that the performance of proposed strategies is significant over each other. Since Friedman's test has been conducted on 17 strategies over 9 functions, the F-statistics value for the confidence level of 95% is extracted from the F-table as 1.7142. The computed F-score value is 10.6583 which is much higher than the F-statistics value. This suggests that the performances of the selected strategies are significantly different from each other and hence, the null hypothesis can be rejected. Furthermore, to highlight the performance of selected strategies and to select the best-suited strategy the post-hoc Bonferroni-Dunn test has been conducted.

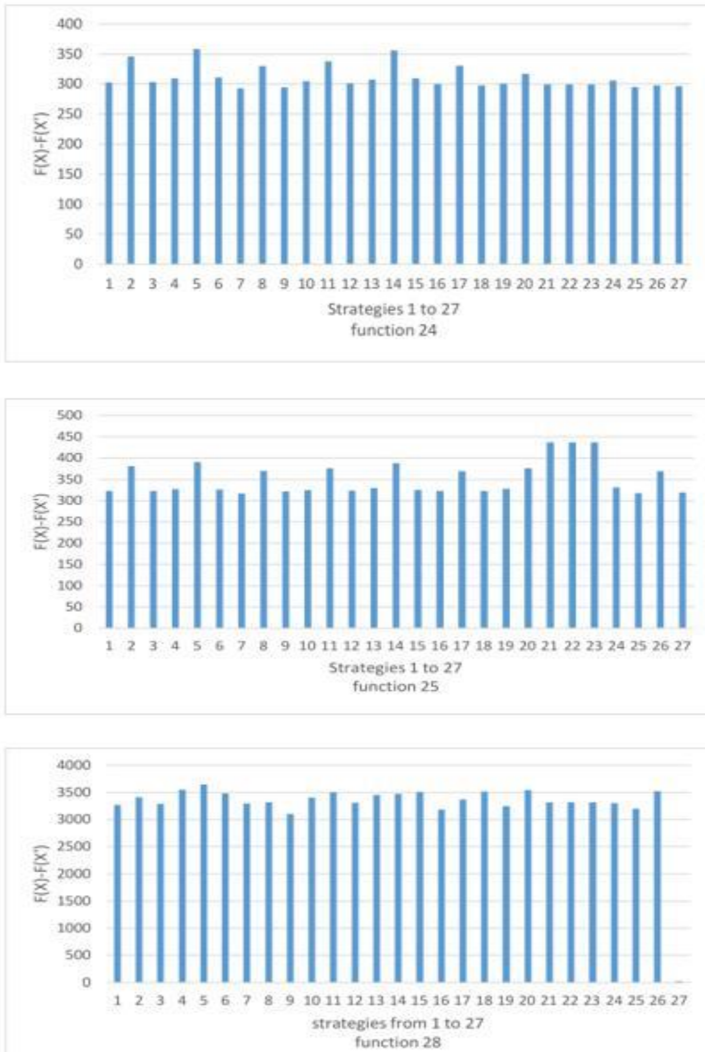

Figure 10: Histograms of all possible strategic settings on functions F24, F25 and F28 of CEC 2013
Source: Authors' Estimation

VI. Results and Discussions

This test provides a Critical Difference (CD) value and if the difference in average ranks of two strategies are more than the CD value then the performance of the strategy with the lowest average rank is significantly better than the ones with higher average ranks. The statistical result is summarized in Table 2 from where it has been observed that the performance of strategies 7, 9, 25, and 27 from Table 1 are significantly better than all the other proposed strategies.

Table 2. Statistical Analysis for Different Strategies ST 1-9 and 19-27

Strategies	Avg Rank Difference w.r.t ST25
ST1	5.1667
ST2	9.1667
ST3	4.8333
ST4	7.7222
ST5	12.7778
ST7	1.0000
ST8	5.6667
ST9	0.7222
ST19	2.7778
ST20	10.2222
ST21	6.6667
ST22	7.5556
ST23	8.7778
ST24	8.9445
ST26	7.6111
ST27	0.5000
Critical Difference	3.2501
F Score (Friedman)	10.6583

This depicts an evident picture that the value of α in GG strategy should be kept higher than 0.8 and β in the SRP strategy should be either random or linearly decreasing (Ld2) with values ranging between 0.2-0.1. Furthermore, SIG must be performed using either 4 or 6 guiders that is the use of Square or Hexagon strategies would generate better results.

A. Comparative Performance Analysis Of Ceho With Other Algorithms

In this section, the performance of CEHO has been compared with a few algorithms on the CEC 2013 benchmark functions. The algorithms which are selected for comparison are elephant herding optimization (EHO) Wang et al. (2016), differential evolution (DE) Trivedi et al. (2017), sine cosine algorithm (SCA) Mirjalili (2016) and whale optimization algorithm (WOA) Mirjalili and Lewis (2016). For this, all the selected algorithms have been tested on 30-dimensional problems with the functions F3, F6, and F9, as shown in Table 3 [29]. In the above Table, it has been observed that CEHO has performed well in all of the above-selected functions of CEC 2013.

VII. CONCLUSION AND FUTURE WORK

In this paper, a new human learning principles-based technique the Cognitive Elephant Herding Optimization (CEHO) has been proposed that has an aim to enhance the performance of the basic EHO algorithm. Incorporating these strategies, twenty-seven different settings have been initially proposed. The best possible setting from the proposed strategies is then extracted through extensive experimental evaluation on the CEC 2013 and finalized with the help of the Bonferroni-Dunn test. CEHO has been compared with WOA, DE, SCA, and EHO and performed well against selected functions. This study can further be tested on other benchmark suits and can be compared with other state-of-the-art algorithms in the future.

Table 3: Mean and Standard Deviation Performances for F3, F6 and F9 CEC 2013 Benchmark Functions

Algorithms		F3		F6		F9
	Mean	**STD.**	**Mean**	**STD.**	**Mean**	**STD.**
WOA	**1.99E+02**	**1.99E+02**	**2.64E+02**	**6.12E+01**	**1.99E+02**	**3.20E+01**
DE	**2.60E+02**	**2.60E+02**	**2.50E+02**	**1.31E+01**	**2.60E+02**	**1.14E+01**
SCA	**2.50E+02**	**2.50E+02**	**2.71E+02**	**2.17E+01**	**2.50E+02**	**1.63E+01**
EHO	**2.69E+02**	**2.69E+02**	**1.26E+02**	**8.03E-01**	**2.69E+02**	**3.35E+00**
CEHO	**9.37E+01**	**9.37E+01**	**1.15E+02**	**3.06E+01**	**9.37E+01**	**2.95E+01**

Source: https://link.springer.com/article/10.1007/s10845-020-01723-6

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CONFLICT OF INTEREST

There is no conflict of interest between all the authors.

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