Normative Improved Artificial Fish Swarm Algorithm (NIAFSA) for Global Optimization

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Abstract: Optimization is an important field of research. Various optimization algorithms have been developed to solve optimization problems. Nevertheless,many have not succeeded to achieve the real global optima. Hence, a research on designing and developing a global search and optimization algorithm is presented in this paper. The aim is to enhance the performance of global and local searching strategy in term of best optimal solution. The fish swarm algorithm with the particle swarm optimization with extended memory (PSOEM-FSA) is hybridized with the normative knowledge to become a normative improved fish swarm algorithm (NIAFSA). The feature of global crossover breeding is installed into the proposed algorithm to achieve relatively consistent results. A random initialization of initial population is introduced to spread out the candidates of artificial fishes (AFs) over the solution space. In addition, parameters such as visual and step are made adaptive along the iteration process to balance the contradiction between global and local search ability. The collected results are analyzed and compared with few existing fish swarm variant algorithms to verify the performance of the proposed algorithm

Index Terms: Artificial fish swarm algorithm (AFSA), adaptive visual and step, particle swarm optimization (PSO), PSO with extended memory (PSOEM), normative knowledge,global crossover

I. INTRODUCTION

Swarm intelligence algorithmsare commonly developed by simulating the behavior of creatures in nature. They have been widely used in different fields of application, such as data mining, knapsack problem solving, etc. The relatively popular algorithms include ant colony optimization algorithm (ACO)[1], [2], particle swarm optimization (PSO) algorithm[3], [4], artificial bee colony (ABC) algorithm [5]–[7]and many more. Artificial fish swarm algorithm (AFSA) is the one of the most recent swarm algorithms, which was originally proposed by Li Xiao-lei, Shao Zhi-jiang and QianJi-xin at 2002 [8].AFSA imitates the behavior process of fish swarm in the real environment, to train the artificial fishes (AFs) to take action according to the real-time situation. Each AF is taught to perform four kinds of basic behavioral patterns: follow, swarm, prey and random behaviors. Follow behavior speeds-up the algorithm convergence.Swarm behavior strengthens the stability and global convergence of the algorithm. Prey behavior plays the role asthe foundation of the algorithm's convergence and the random behavior balances the contradiction among theother three behaviors. Each AF will perform any from those behaviors regarded to its current situation and condition. Generally, AFs gather the information and take a move using the "visual" and "step", in which "visual"is the perception and "step" is the moving step length of each AF.

There is still a huge potential for the development in the field of fish swarm algorithm. The existing fish swarm algorithms have not reached the real optima and extremely superior convergence rate. In this research, an improved algorithm callednormative improved artificial fish swarmalgorithm(NIAFSA) is proposed.The goal is to design a modified fish swarm algorithm that is able to yield better performance. This paper is outlined as follows;Section II reviews the literatures, Section III lays out the methodology of proposed algorithm, Section IV explains the experimental settings and analyzes the computational results, and Section V describes the conclusion of this research.

II. REVIEW

PSOEM-FSA

Touse the information at previous iterations, PSOEM [9] upgraded PSO [3] with the extension of memory.The expressions of PSOEM are denoted as [10]:

$$x_{t+1} = x_t + v_{t+1} \tag{1}$$

and

$$v_{t+1} = \omega v_t + \alpha_t^l[\varphi_t(\rho_t^l - x_t) + \varphi_{t-1}(\rho_{t-1}^l - x_{t-1})] + \alpha_t^g[\varphi_t(\rho_t^g - x_t) + \varphi_{t-1}(\rho_{t-1}^g - x_{t-1})] \tag{2}$$

where ***t*** denotes the index of current iteration, (***t-1***)-th iterative information indicates the extended memory used, v_t represents the speed of the particle in the ***t***-th iterative process, hence v_{t+1} represents its updated speed vector, x_t represents the particle speed in the ***t***-th iterative process, ρ_t^l represents the current individual extreme value point of the particle in the ***t***-th iterative process, ρ_{t-1}^l represents extreme value point of the particle in the (***t-1***)-th iterative process, ρ_t^g represents the current global extreme value point of the population in the ***t***-th iterative process, ρ_{t-1}^g represents the global extreme value point of the population in the (***t-1***)-th iterative process, α_t^l and α_t^g are the acceleration factors, ω is known as the inertia weight, φ_t is called current effective factor, φ_{t-1} is called the effective factor of extended memoryand $\sum \varphi = 1$.

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he behaviors from the standard AFSA[8] are then integrated into PSOEM, whichresulted in the formation of PSOEM-FSA[10]. In PSOEM-FSA, communication behavior pattern and memory behavior pattern have been proposed. Communication behavior pattern trains the artificial fishes (AFs) to swim by referring to the current and previous global optimal position ($X_{gbest}^{t}$and X_{gbest}^{t-1}) of the entire fish. This helps to strengthen the ability in exchanging and sharing information between the individuals in the search process, and further reduces the blindness of the fish in the search process [10].The updated vector of communication behavior in PSOEM-FSA is expressed as follows[10]:

$$v_{t+1} = \omega v_t + rand[0,1] \times step\left[\left(\frac{\varphi_t\left(X_{gbest}^{t}-X_i^t\right)+\varphi_{t-1}\left(X_{gbest}^{t-1}-X_i^{t-1}\right)}{\left|\varphi_t\left(X_{gbest}^{t}-X_i^t\right)+\varphi_{t-1}\left(X_{gbest}^{t-1}-X_i^{t-1}\right)\right|}\right)\right] \quad (3)$$

where v_t represents the speed of the individual in the ***t***-th iterative process, hence v_{t+1} represents its updated speed vector, X_{gbest}^{t} represents the current global extreme value point of the population in the ***t***-th iterative process, X_{gbest}^{t-1} represents the global extreme value point of the population in the (***t-1***)-th iterative process and X_i^t represents the current position vector of ***i***-th individual in ***t***-th iterative process.

Memory behavior pattern trains the AFs to swim while referring to its own optimal positions ($X_{lbest}^{t}$and X_{lbest}^{t-1}). It definitely helps to reduce the blindness of the fish in the local searching process [10].The updated vector of memory behavior is expressed as follows[10]:

$$v_{t+1} = \omega v_t + rand[0,1] \times step\left[\left(\frac{\varphi_t(X_{lbest}^{t}-X_i^t)+\varphi_{t-1}(X_{lbest}^{t-1}-X_i^{t-1})}{|\varphi_t(X_{lbest}^{t}-X_i^t)+\varphi_{t-1}(X_{lbest}^{t-1}-X_i^{t-1})|}\right)\right] \quad (4)$$

where X_{lbest}^{t} represents the current individual extreme value point of the particle in the ***t***-th iterative process and X_{lbest}^{t-1} represents the global extreme value point of the population in the (***t-1***)-th iterative process.

Normative Knowledge

Cultural artificial fish swarm algorithm (CAFSA)[11] involves the implementation of the normative knowledge. Normative knowledge is a set of promising variable range that provides standards for individual behaviors and guidelines within which individual adjustments can be made [12]. It is a set of information for each variable which describes a feasible solution space of an optimization problem.

n-th dimensional vector $\boldsymbol{I_j}$ denotes the closed interval for variable $\boldsymbol{j} \in (1, 2\ldots n)$, which is expressed as:

$$I_j = [l_j, u_j] = \{x | l_j \le x \le u_j\} \quad (5)$$

wherel_j and u_j are lower and upper bounds of feasible space for ***j***-th variable, respectively. l_j and u_j are initialized with lower and upper bounds of individuals [11]. According to the theorem of normative knowledge,l_j and u_j are updated based on the following expressions [11]:

$$l_j^{t+1} = \begin{cases} x_{i,j}, x_{i,j} < l_j^t \ or \ f(X_i^t) < L_j^t \\ l_j^t, otherwise \end{cases}$$

$$u_j^{t+1} = \begin{cases} x_{k,j}, x_{k,j} \ge u_j^t \ or \ f(X_k^t) < U_j^t \\ u_j^t, otherwise \end{cases} \quad (6)$$

where***i***-th individual affects the lower bound for variable ***j***, ***k***-th individual affects the upper bound for variable ***j***, L_j^t and U_j^t are the values of the fitness function associated with the bounds l_j^t and u_j^t,respectively for ***t***-th iteration process [11]. The fitness functions L_j^t and U_j^t are updated as follows [11]:

$$L_j^{t+1} = \begin{cases} f(X_i^t), x_{i,j} < l_j^t \ or \ f(X_i^t) < L_j^t \\ L_j^t, otherwise \end{cases}$$

$$U_j^{t+1} = \begin{cases} f(X_k^t), x_{k,j} \ge u_j^t \ or \ f(X_k^t) < U_j^t \\ U_j^t, otherwise \end{cases} \quad (7)$$

III. PROPOSED ALGORITHM

The proposed NIAFSA hybridizes the characteristics of PSOEM-FSA [10] with the normative knowledge which isimplemented in the cultural artificial fish swarm algorithm (CAFSA) [11]. It improves the technique in adapting parameters, mainly on ***"visual"/"step"***and ***"visual$_{min}$"/"step$_{min}$"***along the iteration process. In addition, the global crossover breeding technique is introduced.

NIAFSA involves the following stages:

Step 1: Randomly initialize artificial fishes (AFs) population, Randomly initialize artificial fishes (AFs) population, position of the fishes, the optimal locations of each fish's memory and the global optimal position parameters.

Step 2: Execute four association behavior models in parallel: follow or prey behavior, swarm or prey behavior, normative communication or prey behavior and normative memory or prey behavior. Each behavior model yields distinct updated location and solution.

Step 3: Greedy select the optimal association behavior and update the current location of AFs.

Step 4: Update the current global, local optima and current global, local extreme points in bulletin board.

Step 5: If the global optimal value is not updated for $\boldsymbol{t_{limit}}$ times, gradient decline the "***visual$_{min}$***" and "***step$_{min}$***" and comply global crossover to hatch a superior offspring, otherwise go to step 6.

Step 6: Adapt the ***"visual"*** and ***"step"*** parameters.

Step 7: If the maximum iteration number is reached, the optimization process ends, otherwise go to Step 2.

The following sub-sections explain the framework of the newly designed features in NIAFSA. Sub-section A explains normative communication behavior, sub-section B explains normative memory behavior, sub-section C describes the improved adaptive parameters and sub-section D depicts the structure of global crossover breeding in NIAFSA.

Normative Communication Behavior

The global and local searches in PSOEM-FSA involved the employed extended memory. AF tends to refer to theprevious guideline to decide on an accurate direction. Yet, some insufficiencies were found in equation (3), regardingthe communication behavior.The search direction

is totally dependent upon the global extreme point $X_{gbest}^{t}$and X_{gbest}^{t-1}, causingalack of flexibility in the global search action.

Hence, further improvements are proposed to enhance the communication behavior pattern (equation (3)).

The reconnaissance is executed around the global extreme point$X_{gbest}^{t}$to find a complementary guideline other than global optima to cite an even more accurate direction and further reduces the blindness of AFs. The reconnaissance radius is a set of variable range of feasible space [$\boldsymbol{l_j}$, $\boldsymbol{u_j}$] based on the normative knowledge theorem. Some transformations are made to vary the feasible space [$\boldsymbol{l_j}$, $\boldsymbol{u_j}$] to accommodate the strengthened behavior pattern. $l_j$andu_j are basically initialized with initial lower and upper bounds, $l_j^{initial,t=1}$ and $u_j^{initial,t=1}$, respectively andthey are updated as follows:

$$l_j^{t+1} = \begin{cases} \min(X_j^{t+1}), \min(X_j^{t+1}) > l_j^t \\ l_j^t, otherwise \end{cases}$$

$$u_j^{t+1} = \begin{cases} \max(X_j^{t+1}), \max(X_j^{t+1}) < u_j^t \\ u_j^t, otherwise \end{cases} \quad (8)$$

where$\boldsymbol{j}$ denotes the variable of dimension, $\boldsymbol{j} \in (1, 2 \dots \boldsymbol{N})$, $\boldsymbol{t}$ denotes index of iteration, X_j^{t+1} represents the position vectors of individuals for $\boldsymbol{j}$-th dimension in ($\boldsymbol{t+1}$)-th iterative process, l_j^{t+1} is the lower bound for $\boldsymbol{j}$-th dimension in ($\boldsymbol{t+1}$)-th iterative process and u_j^{t+1} is the upper bound for $\boldsymbol{j}$-th dimension in ($\boldsymbol{t+1}$)-th iterative process.

The reconnaissance radius and the selective method of complementary guideline are presented as follows:

$$radius^t = distance[l^t, u^t] \quad (9)$$

and

$$X_g^t = X_{gbest}^t + rand[-1,1] \times radius^t$$

$$X_g^t = \begin{cases} X_g^t, f(X_g^t) < f(X_{gbest}^t) \\ X_i^t, otherwise \end{cases} \quad (10)$$

where$\boldsymbol{t}$ denotes the index of iteration, X_g^t is a selected guideline within the reconnaissance radius, X_{gbest}^t represents the current global extreme value point of the population in the $\boldsymbol{t}$-th iterative process and X_i^t represents the current position vector of $\boldsymbol{i}$-th individual in $\boldsymbol{t}$-th iterative process.

For normative communication behavior pattern, the updated position vector can be expressed as follows:

$$X_i^{t+1} = X_i^t + rand[0,1] \times step\left[\alpha_{g1}\left(\frac{(X_g^t - X_i^t)}{|(X_g^t - X_i^t)|}\right) + \right.$$

αg2φtXgbestt−Xit+φt−1Xgbestt−1−Xit−1φtXgbest t−Xit+φt−1Xgbestt−1−Xit−1 (11)

whereα_{g1} and α_{g2} are known as the speed factors, φ_t is called current effective factors, φ_{t-1} is called the effective factor of extended memory, $\sum \alpha_g = 1$ and $\sum \varphi = 1$.

Normative Memory Behavior (AF_NORM_MEMORY)

Normative memory behavior is quite similar to the normative communication behavior. Just that, normative memory behavior emphasizes the global searching action, while normative memory behavior emphasizes the delicate local search. The reconnaissance is executed around the local extreme point X_{lbest}^t to find a complementary guideline other than individuals' own optimato cite an even more precise direction to further increase local search's efficiency. The parameters l_j and u_j are updated based on equation (8) and the reconnaissance radius is expressed as equation (9).The current and previous local extreme location X_{lbest}^t and X_{lbest}^{t-1} have replaced the global extreme location, X_{gbest}^t and X_{gbest}^{t-1} respectively. Hence, the selective method of new guideline ispresented as follows:

$$X_g^t = X_{lbest}^t + rand[-1,1] \times radius^t$$

$$X_g^t = \begin{cases} X_g^t, f(X_g^t) < f(X_{gbest}^t) \\ X_i^t, otherwise \end{cases} \quad (12)$$

where X_g^t is a new selected guideline innormative memory behavior, X_{lbest}^t represents the current individual extreme value point of the particle in the $\boldsymbol{t}$-th iterative process and X_i^t represents the current position vector of $\boldsymbol{i}$-th individual in $\boldsymbol{t}$-th iterative process.

As for normative memory behavior pattern, the updated position vector can be expressed as follows:

$$X_i^{t+1} = X_i^t + rand[0,1] \times step\left[\alpha_{g1}\left(\frac{(X_g^t - X_i^t)}{|(X_g^t - X_i^t)|}\right) + \right.$$

αg2φtXlbestt−Xit+φt−1Xlbestt−1−Xit−1φtXlbestt −Xit+φt−1Xlbestt−1−Xit−1 (13)

Improved Adaptive Parameters

The improved method in literature[13] has been reviewed to balance the contradiction between global search ability and local search ability of AFSA. Relatively large "***visual***" and "***step***" are adopted at early iterative process to enhance the global search ability and speeds-up the convergence rate of the algorithm[14]. During the iterations, these parameters are declined to improve the local search of the algorithm. After modification, the decrements of parameters are as presented:

$$\begin{cases} visual^{t+1} = visual^t - visual^t * \lambda + visual_{min} \\ step^{t+1} = step^t - step^t * \lambda + step_{min} \\ \lambda = \exp\left(-\frac{\sigma}{\sqrt[4]{(t_{max})^3}} * (t_{max} - t)\right) \end{cases} \quad (14)$$

where$visual_{min}$ is the minimum visual value, $step_{min}$ is the minimum step value, $t \in (1,2 \dots t_{max})$ and $\sigma < 1$ at any stage.

"Visual$_{min}$" and ***"step$_{min}$"***aresafety featuresto the iterative variation of***"visual"*** and ***"step"***. Without the presence of ***"visual$_{min}$"*** and ***"step$_{min}$"*** in equation (14), ***"visual"*** and ***"step"*** will definitely drop to an approximately zero value at later stage. If this happens, artificial fishes (AFs) will lose the ability to perform any further local search, as they fail to perform any significant move.

Yet, it is always problematic to set the values of ***"visual$_{min}$"*** and ***"step$_{min}$"***. If large***"visual$_{min}$"*** and ***"step$_{min}$"*** are set, it may affect the accuracy of local search, but small***"visual$_{min}$"*** and ***"step$_{min}$"*** may consume more time to reach the exact optimum. Hence, the ***"visual$_{min}$"*** and ***"step$_{min}$"*** are proposed to be gradient declined under certain condition, where theoptimum remains the same without updating after a given limitation of iterations. The declinations of both parameters are presented as follows:

$$visual_{min}^{t+1} = \frac{visual_{min}^t}{0.5 \times \sqrt[3]{t_{max}}} \quad (15)$$

and

$$step_{min}^{t+1} = \frac{step_{min}^t}{\sqrt[3]{t_{max}}} \quad (16)$$

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where $t \in (1,2 \ldots t_{max})$ is the iteration number.

Global Crossover Breeding

In multi-modal optimization functions, there is a high possibility to be trapped inside a local optimum, especially in multi-dimensional functions. To escape from a local optimum, sharing of information is necessary. Global crossover breeding is a proposed technique to do so. It generates a superior offspring which holds brilliant information taken from both parent candidates.

Global crossover breeding includes global optima as a candidate of parent vector in crossover process. The primary parent candidates are chosen from the individuals of AFs: one candidate is decided to be the current best performed AF and the other one is a random chosen AF. Chosen individual's vector is at prior, followed by global optima vector. The global crossover breeding is expressed as:

$$X_{new,j}^{t+1} \begin{cases} X_{k,j}^{t+1}, & if\ r_1 \le r_2\ or\ j = D_j \\ v_{new,j}^{t+1}, & otherwise \end{cases}$$

$$v_{new,j}^{t+1} \begin{cases} X_{gbest,j}^{t+1}, & if\ r_3 \le r_4 \\ X_{i,j}^{t+1}, & otherwise \end{cases} \quad (17)$$

where ***i***-th individual is the current best performed candidate, ***k***-th individual is the random chosen candidate, ***j*** denotes as the index of dimension, ***t*** denotes the index of iteration, $X_{gbest,j}^{t+1}$ indicates the global optima vector at ***j***-th dimension in (***t+1***)-th iterative process, $X_{i,j}^{t+1}$ represents the position vector of ***i***-th individual at ***j***-th dimension in (***t+1***)-th iterative process, $X_{k,j}^{t+1}$ represents the position vector of ***k***-th individual at ***j***-th dimension in (***t+1***)-th iterative process, r_1, r_2, r_3 and r_4 are denoted as different random number and $D_j = 1$.

IV. RESULTS AND DISCUSSION

Experiemental Setting

Although the algorithm isimplemented to be user-dependent, for the purpose of validation and fair comparison with other works, the parameters used are adopted from[15]. Table 1 displays the parameter settings for NIAFSA. The maximum iteration number, $\boldsymbol{t_{max}}$= 1000 has been used to carry out the evaluations. In order to obtain the means and standard deviations (SD) of best optimal solutions for each function, NIAFSAhas been proposed to run 10 times for each benchmark function.

Ten optimization benchmark functions are used to evaluate the performance of NIAFSA. The representation of the benchmark functions is listed as:$f_1 = f_{Ackley}(x)$, $f_2 = f_{Alipine}(x)$, $f_3 = f_{Griewank}(x)$, $f_4 = f_{Levy}(x)$, $f_5 = f_{Quadric}(x)$, $f_6 = f_{Rastrigin}(x)$, $f_7 = f_{Rosenbrock}(x)$, $f_8 = f_{Elliptic}(x)$, $f_9 = f_{Sphere}(x)$, $f_{10} = f_{SumPower}(x)$.

Table 1: Parameter Settings

	Parameter	**NIAFSA**
Standard AFSA	No. of tries	50
	Visual	$0.75 \times (L - U)$
	Step	$0.8 \times Visual$
	Crowding factor, δ	0.75
	Dimension, N	10
	Fish Population, n	50
PSOEM-FSA	φ_t	0.5
	φ_{t-1}	0.5
NIAFSA	α_{g1}	0.6
	α_{g2}	0.4
	$visual_{min}$	$10^{-6}\sqrt{(L-U) \times N}$
	$step_{min}$	$10^{-6}\sqrt{(L-U) \times N}$
	σ	0.88
	t_{limit}	$0.02 \times \boldsymbol{t_{max}}$

Validation of NIAFSA

NIAFSA shows the result of NIAFSA performance on each benchmark function in Table 2. It has to be noted that the closer the data values with reference to its global minimum, the better the performance of NIAFSA in specific function. As reviewed from Table 2, NIAFSA has perfect results on Rastrigin function ($\boldsymbol{f_6}$) which is always difficult to be solved. It tends to reach the real global minimum in every run of simulations, showing the best results among all the test bench functions. This certifies the contribution of "global crossover" in helping to escape from local optimum.

As observed from Table 2, NIAFSA has been compared with related algorithms, mainly PSOEM-FSA [10] and CIAFSA [16], under the same maximum iteration number, $\boldsymbol{t_{max}}$. Both PSOEM-FSA and CIAFSA exhibit the same characteristics of communication behavior and memory behavior which is the origin of the proposed features in NIAFSA – normative communication behavior and normative memory behavior. They are suited to be used to test the contributions of proposed normative communication and memory behavior.

Table 2: NIAFSA performance comparison with related algorithms on benchmark functions

		Variants			
	Ind.	NIAFSA	PSOEM-FSA [10], [16]	CIAFSA [16]	AFSA [16]
f_1	Best	4.44E-15	1.68E-07	1.79E-06	2.50E- 04
	Mean	4.8E-15	1.02E-04	3.56E-04	3.09E-02
	SD	1.12E-15	1.11E-04	3.95E-04	1.94E- 02
f_2	Best	3.52E-32	4.79E-07	1.94E-06	6.41E-08
	Mean	4.47E-16	6.87E-06	8.98E-06	4.14E-06
	SD	4.46E-16	5.39E-06	1.18E-05	3.62E- 06
f_3	Best	0	2.94E-08	7.47E-06	2.49E-09
	Mean	1.89E-02	1.07E-01	1.52E-02	7.11E- 06
	SD	1.92E-02	1.84E-01	3.47E-01	7.57E-05
f_4	Best	1.50E-32	4.79E-07	1.94E-06	1.38E- 08
	Mean	1.50E-32	6.87E-06	8.98E-06	2.34E- 05
	SD	0	5.39E-06	1.18E-05	2.63E- 05
f_5	Best	8.67E-33	1.16E-08	9.04E-05	1.98E- 08
	Mean	1.54E-13	1.16E-04	9.34E+00	5.44E-05
	SD	4.00E-13	2.63E-05	2.11E+01	1.29E-04
f_6	Best	0	3.09E-10	4.56E-09	3.20E-10
	Mean	0	8.34E-06	2.06E-06	2.38E-07
	SD	0	2.40E-05	4.55E-06	4.44E- 07
f_7	Best	2.37E-09	1.99E-14	2.54E-14	5.65E-12
	Mean	3.99E-01	6.55E-10	1.45E-05	4.26E-08
	SD	1.26E-00	1.87E-10	3.81E-05	7.70E- 08

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f_8	Best	1.78E-50	1.03E-02	2.18E+01	1.61E-07
	Mean	2.18E-22	5.73E+00	8.40E+03	3.29E-02
	SD	6.88E-22	1.04E+01	3.51E+03	6.57E- 02
f_9	Best	3.86E-57	3.08E-13	1.00E-12	1.58E- 11
	Mean	2.74E-54	6.19E-08	6.51E-03	1.21E-07
	SD	4.59E-54	1.11E-07	2.59E-03	1.84E-07
f_{10}	Best	1.62E-73	1.43E-15	4.57E-13	2.94E-14
	Mean	3.79E-49	9.70E-10	1.72E-09	6.47E- 12
	SD	1.18E-48	1.69E-09	3.47E-09	1.38E- 11

The bold data values in Table 2 represent the best results in each function among different algorithms. Aside from Rosenbrock function (f_7),the proposed NIAFSAoutperforms PSOEM-FSA, CIAFSA and AFSA. Especially in Ackey, Alipine, Levy, Quadric,Rastrigin, Elliptic, Sphere and SumPower functions (f_1, f_2,f_4, f_5,f_6, f_8, f_9, f_{10}), NIAFSAachieves relatively superior best optima and mean results over other algorithms, affirming the truth of NIAFSA tended to arrive to the respective global minimum. Also, the small standard deviation (SD) values show the high quality of precision in NIAFSA.

V. CONCLUSION

The work has successfully developed the proposed Normative Improved Artificial Fish Swarm Algorithm (NIAFSA). Numerical simulation experiments were performed to compare its performance with the predecessor of this proposed algorithm: PSOEM-FSA and CIAFSA. The experimental results showed that NIAFSA performed competitively in comparison to its predecessors and its standard algorithm in terms of global optimum achievement.

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