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Drosophila Food-Search Optimization

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ABSTRACT

The method of finding optimal solution to an optimization problem is a recent challenge for the researchers. In order to solve an optimization problem many evolutionary methods have been introduced as alternate paradigms. In this paper an extensive efforts has been made to solve unconstrained optimization problems by proposing a new algorithm namely Drosophila Food-Search Optimization (DFO) Algorithm. DFO mimics the food-search mechanism of a fly in nature based on called *Drosophila Melanogaster*. To maintain the diversity throughout the population during simulation, an exploration operation has been developed to generate new individuals. A set of well known benchmark function have been used to validate the better performance of DFO. The experimental results confirms that the proposed technique DFO performs better than some well known existing algorithms like Differential Evolution (DE), Intersect Mutation Differential Evolution (IMDE) algorithm, self-adaptive DE (JDE), improved Particle Swarm Optimization (PSO) algorithms, Artificial Bee Colony (ABC) algorithm and Bee Swarm Optimization (BSO) algorithm. Further two real world problems namely Gas Transmission Compressor Design and Optimal Capacity of Gas production facilities are considered and the better performance of DFO is confirmed.

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1. Introduction

Optimization is ubiquitous and spontaneous process that performs on integral part of our day to day life. In the most basic sense, it can be defined as an art of selecting the best alternatives among a given set of options. These problems arise in various disciplines such as engineering designs, agricultural sciences, manufacturing systems, economics, physical sciences, pattern recognition, etc. In view of practical utility in solving optimization problem, an efficient/robust computational method is essential.

In spite of the existence of a number of deterministic methods, the probabilistic/evolutionary approaches based on nature inspired analogy became more popular in recent years, as they do not need any auxiliary information like differentiability and continuity of the problem in hand. Among them, the most referred algorithms in the literature are Genetic Algorithm (GA) [1], Particle Swarm Optimization (PSO) [2], Differential Evolution (DE) [3], Ant Colony Optimization (ACO) [4], Evolutionary Programming (EP) [5], Diversity Guided Evolutionary Programming (DGEP) [6], Self-Adaptive DE (JDE) [7], Fruit Fly Optimization Algorithm (FOA) [8], Structural Optimization (SO) [9], etc. However, most of these methods suffer with the involvement of (i) complicated mechanism, (ii) computational burdensome, (iii) premature convergence, (iv) trapping in some local minima and (v) fine tuning of many parameters. In order to minimize these shortcoming to some extent, an extensive efforts is made in this paper by introducing a new and robust technique namely Drosophila Food-Search Optimization (DFO) Algorithm. DFO mimics the food-search mechanism of a fly to search the food with a minimal effort. The detailed description presented in Section 2.

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The rest of this paper is organized as follows. The Section 2 introduces the food searching mechanism of Drosophila. Section 3 defines some additional components used in the proposed technique. Section 4 introduces the Drosophila Food-Search Optimization (DFO) Algorithm. In the Section 5, numerical results and their analysis are presented. Two different real life problems are discussed in Section 6. Lastly, the conclusion of this paper is drawn in Section 7.

2. *Drosophila Melanogaster*

D. Melanogaster is a fly in nature that has approximately 3 mm long and is used as the model organism for research in genetics. It is considered as a classical insect model for studying many sensory systems, including taste and olfaction [14,15]. Coincidently, the fruit fly has food preferences as dislike similar to those of humans. They are depend on hair-like structure, called sensilla, located on multiple parts of their body including proboscis, wing margins, legs and ovipositor [15] (shown in Fig. 1). Each of these receptors contains gustatory receptors neurons (GRNs) that help fruit fly to select nutrient food and select mates [16,21]. These receptors are especially used to sense the difference between compound with high sugar content and those with high salt content. The two-choice preference test, first developed by Tanimura and co-workers [19], is a simple but powerful assay for measuring feeding behavior.

The Drosophila ingests food through its proboscis (shown in Fig. 2), which consists of a muscular tube, the pharynx, gated by two labial palps (labellum) and the palp located at the distal end of the proboscis. Each palp is covered with 31 stereotypically arranged taste bristles (called sensilla) [18] (shown in Fig. 3). Sensilla are of two types namely internal sensilla and external sensilla. The external sensilla detect preferable food sources and the internal sensila check the foods before it allow into the digestive system. The specific role of this internal sensilla might serve either as sensors for harmful substances that, if activated elicit a 'regurgitate' responses, or alternatively, to verify desirable substances and promote sucking reflexes. The proboscis extension reflex is a more direct measure to taste response of specific GRNs, as opposed to the overall perception at an organism level [14,17,20].

The Drosophila also consists with highly well characterized olfactory receptors [22–24] (shown in Fig. 4). More than 60 Drosophila olfactory receptors (DOR) genes [25] encode a family of seven transmembrane G-protein coupled receptors, whose function recognizes specific odorant molecules. The DORs are expressed in dendrites of olfactory receptor neurons (ORNs) housed in sensilla located on the antennae and the maxillary palps, the two olfactory organs of Drosophila. The olfactory receptor neurons (ORNs), the space between the dendrite and the inner surface of the bristle filled with lymph, a secretion from support cells that are associated with each taste sensillum [26]. Little is known about the composition of taste lymph, but it is likely to have similar functions as the lymph of olfactory sensilla which is thought to modulate accessibility of odorants to their cognate receptors [14,15]. Indeed, several odorant binding proteins are also expressed in taste sensilla [16,17] and might play a general role in shuttling both volatile and soluble chemicals from the environment to the dendrite of chemosensory neurons which express specific gustatory receptors.

Fig. 1. *Drosophila Melanogaster*.

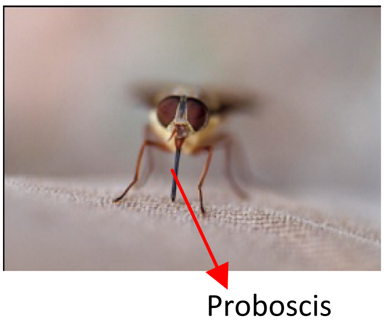

Fig. 2. Gustatory receptors.

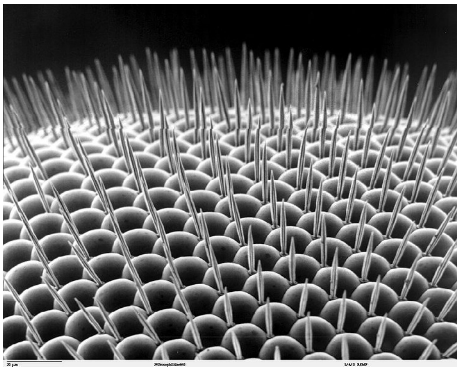

Fig. 3. Taste bristles (Sensilla).

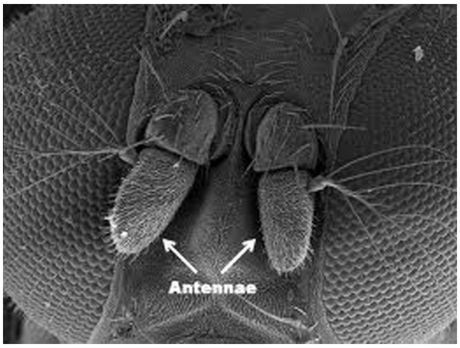

Fig. 4. Olfactory receptors.

2.1. Ligand

A ligand is a molecular substance (a small molecule) that forms a ‘complex’ when attached with bio molecule, used for biological purpose (shown in Fig. 5). It is also used as a signal triggering molecule in connection with protein binding [30]. When ligand binds with a receptor (receptor protein), it alerts chemical conformation. The conformational state of a receptor protein determines its functional state. The tendency or strength of binding is called affinity. In general, high-affinity ligand binding means greater intermolecular force between the ligand and its receptor. In the other hand, high affinity ligand binding implies that a relatively low concentration of a ligand is adequate to maximally occupy a ligand binding site where as for low affinity binding, a relatively high concentration of ligand required before the binding site is maximally occupied and the maximum physiological response to the ligand is achieved.

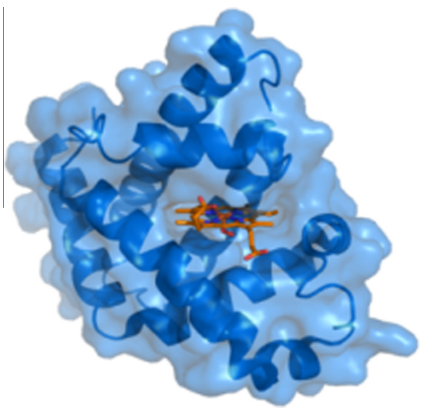

Fig. 5. Structure of ligands.

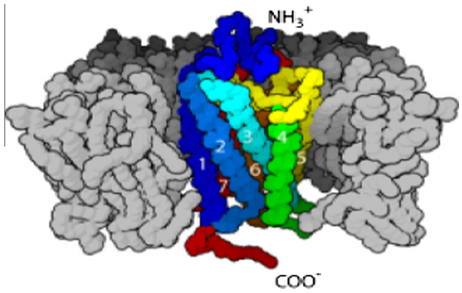

Fig. 6. Molecular structure of G-protein-coupled-receptors.

2.2. G-protein-coupled-receptor

G-protein-coupled-receptor (GPCR) is a large protein family of receptors which recognizes a specific odorant molecules [27] outside the cell and activate inside signal transduction pathways (shown in Fig. 6) and ultimately, cellular responses. It is also known as seven-transmembrane domain receptors because it passes through the cell membrane seven times. The exact size of GPCR super family is unknown but nearly 800 different human genes have been predicted from genome sequences analysis [28,29]. GPCR are integral membrane proteins that possess seven membrane spanning domains and some of them contain ion channels, within their protein. There are two principle signal transduction pathways involving the G-protein coupled receptors namely cAMP (cyclic Adenosine Mono Phosphate) signal pathway and the phosphatidylinositol signal pathway. When a ligand binds with a GPCR, a conformation changes occur in GPCR i.e. it mechanically activates the G protein (also known as *guanine nucleotide-binding proteins* are a family of proteins involved in transmitting chemical signals originating from outside a cell into the inside of the cell), which detaches from the receptors. The receptor can now either activate another G protein or switch back to its inactive state.

3. Some components used in proposed method

3.1. The proposed Redundant Search (RS)

In the past few decades researchers developed many exploration and exploitations techniques namely RCMA [10], NSDE [11,12], LSRCMA [13], DGM [6]. However, to enhance the search capability further and to maintain the diversity in the population, a new search technique namely the Redundant Search (RS) is proposed in this section. The working principle of RS is as per the following steps.

Step 1: Given a population of size P with dimension D. Let the population matrix be taken as $V_{i,j}$ for $i = 1,2,\dots,P$ and $j = 1,2,\dots,D$.
Step 2: Generate random numbers $r1$, $r2 \in [1,D]$ and $r3$, $r4 \in [1,P]$, provided $r1 \neq r2$ and $r3 \neq r4$.
Step 3: Each individual of the population contributes two different individuals by the concept of neighborhood searching. Thus two new populations $U_{i,j}$ and $W_{i,j}$ are being generated from the current population. For each $i = 1, 2, \dots, P$; the following mechanism as follows:

$$U_{i,k} = V_{i,k} + |V_{r3,k} - V_{r4,k}| \tag{1}$$

$$W_{i,k} = V_{i,k} - |V_{r3,k} - V_{r4,k}|, \quad \text{for } k = r1 \quad \text{and} \quad r2. \tag{2}$$

For $j \neq r1$ and $j \neq r2$, $U_{i,j} = V_{i,j}$ and $W_{i,j} = V_{i,j}$
Step 4: The new individuals for the new population are given by.

$$V^{/}_{i,j} = \text{Min}\{f(V_{i,j}), f(U_{i,j}), f(W_{i,j})\} \quad \text{for } i = 1, 2, \dots, P \quad \text{and} \quad j = 1, 2, \dots, D. \tag{3}$$

3.2. Modified Quadratic Approximation (mQA)

A Random Search Technique (RST) for global optimization was first introduced by Mohan and Shankar [34]. Later it is modified as Quadratic Approximation (QA) [36]. In QA, one 'Child' is generated from the selection of three parents R_1, R_2 and R_3 as Eq. (4), where R_1 is considered as best fit individuals and R_2, R_3 are random.

$$\text{Child} = 0.5 * \left(\frac{(R_2^2 - R_3^2)f(R_1) + (R_3^2 - R_1^2)f(R_2) + (R_1^2 - R_2^2)f(R_3)}{(R_2 - R_3)f(R_1) + (R_3 - R_1)f(R_2) + (R_1 - R_2)f(R_3)} \right), \quad (4)$$

where $f(R_1)$, $f(R_2)$ and $f(R_3)$ are the function values at R_1, R_2 and R_3, respectively.

In this paper, a modified Quadratic Approximation (abbreviated as mQA) is proposed. Unlike QA, mQA picks R_1, R_2 and R_3 randomly with a condition that $R_1 \neq R_2 \neq R_3$. Rest mechanism of mQA remains the same as QA. It is experimentally verified that the proposed DFO (Section 4) works better with mQA than DFO with QA (shown later in Section 5.2).

4. Drosophila Food-Search Optimization (DFO)

Based on food searching behavior of *D. Melanogaster*, a new algorithm for finding global optimization namely Drosophila Food-Search Optimization (DFO) is proposed in this section. The Drosophila with its rich history in genetic is superior to the

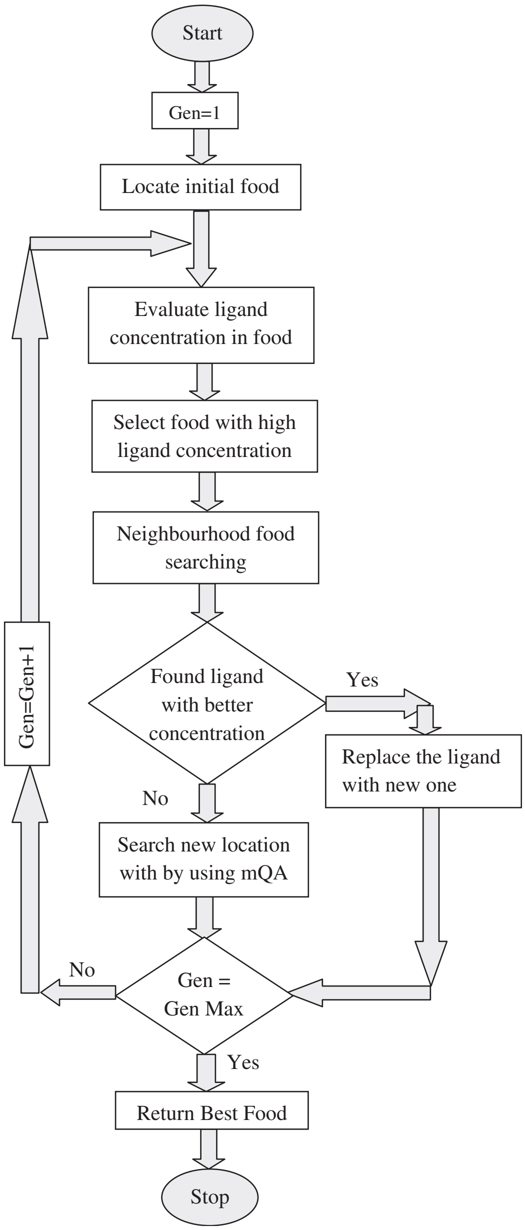

Fig. 7. Flow chart of Drosophila Food-Search Optimization.

other species, especially in sensory system including taste and olfaction. The olfactory receptors of fruit fly can sense all kinds of food sources whose scents blowing in the air. Initially, after getting the food sources, the gustatory receptors (GRs) present in the external sensilla of proboscis check the preferences of the food sources and then passed signal to the internal sensilla that whether it is allowed in digestive system or not. The internal sensilla consisting of GPCR, a large protein family of receptors that sense molecules outside the cell and activate inside signal transduction pathway, with the help of ligand binding [38]. Every molecules of food sources act as a ligand but affinity of protein binding of GPCR with ligand depends on the concentration of ligand. So, if the concentration of the ligand is high, than GPCR will be activated and generate the signal, that enters the SOG region of the brain via nervous system and further analysis takes place there. When the signal input is more, then the SOG region automatically provides positive signal to the proboscis to take the food and due to high prefer ability of the food, the signal input is more and then Drosophila flies towards the food. Therefore, the optimize food-search behavior of Drosophila is characterized and modeled into the population based algorithm as per following steps.

Table 1
Benchmark functions – Series-1 (*S*: domain of the variables, $f_{\min}$: global minima, *C*: function characteristics, *U*: unimodal, *M*: multimodal, *S*: separable, *N*: non-separable) taken from [31].

f	Function	Formulation	S	C	$f_{\min}$
f_1	Sphere	$f(x)=\sum_{i=1}^{D}x_i^2$	$[-100,100]$	US	0
f_2	Schwefel 2.22	$f(x)=\sum_{i=1}^{D}\lvert x_i\rvert+\prod_{i=1}^{D}\lvert x_i\rvert$	$[-10,10]$	UN	0
f_3	Schwefel 1.2	$f(x)=\sum_{i=1}^{D}(\sum_{j=1}^{i}X_i^2)$	$[-100,100]$	UN	0
f_4	Schwefel2.21	$f(x)=\max_i\{\lvert x_i\rvert, 1\leqslant i\leqslant D\}$	$[-100,100]$	US	0
f_5	Rosenbrock	$f(x)=\sum_{i=1}^{D-1}(100(x_{i+1}-x_i^2)^2+(x_i-1)^2)$	$[-30,30]$	UN	0
f_6	Step	$f(x)=\sum_{i=1}^{D}(x_i+0.5)^2$	$[-100,100]$	US	0
f_7	Quartic	$f(x)=\sum_{i=1}^{D}ix_i^4+random[0,1)$	$[-1.28,1.28]$	US	0
f_8	Schwefel	$f(x)=-\sum_{i=1}^{D}(x_i\sin\sqrt{\lvert x_i\rvert})$	$[-500,500]$	MS	−12,569.5
f_9	Rastrigin	$f(x)=10D+\sum_{i=1}^{D}(x_i^2-10\cos(2\pi x_i))$	$[-5.12,5.12]$	MS	0
f_{10}	Ackley	$f(x)=20+e-20e^{-\left(\frac{1}{5}\sqrt{\frac{1}{D}\sum_{i=1}^{D}x_i^2}\right)}-e^{-\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right)}$	$[-32,32]$	MN	0
f_{11}	Griewank	$f(x)=\sum_{i=1}^{D}\frac{x_i^2}{4000}-\prod_{i=1}^{D}\cos(\frac{x_i}{\sqrt{i}})-1$	$[-600,600]$	MN	0
f_{12}	Penalized	$f(x)=\frac{\pi}{D}\{10\sin^2(\pi y_1)+\sum_{i=1}^{D-1}(y_i-1)^2[1+10\sin^2(3\pi y_{i+1})]+(y_D-1)^2\}$ $+\sum_{i=1}^{D}u(x_i,10,100,4)$ where $y_i=1+\frac{1}{4}(x_i+1)$ and $u(x_i,a,k,m)=\begin{cases}k(x_i-a)^m, & x_i>a\\ 0, & -a\leqslant x_i\leqslant a\\ k(-x_i-a)^m, & x_i<-a\end{cases}$	$[-50,50]$	MN	0
f_{13}	Penalize 2	$f(x)=0.1\{\sin^2(\pi x_1)+\sum_{i=1}^{D-1}(x_i-1)^2[1+\sin^2(3\pi x_{i+1})]$ $+(x_D-1)^2[1+\sin^2(2\pi x_D)]\}+\sum_{i=1}^{D}u(x_i,5,100,4)$	$[-50,50]$	MN	0
f_{14}	Foxholes	$f(x)=\left[\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i-a_{ij})^6}\right]^{-1}$	$[-65.536,65.536]$	MS	0.998004
f_{15}	Kowalik	$f(x)=\sum_{i=1}^{11}\left[a_i-\frac{x_1(b_i^2+b_ix_2)}{b_i^2+b_ix_3+x_4}\right]^2$	$[-5,5]$	MN	0.0003075
f_{16}	Six HumpCamel Back	$f(x)=4x_1^2-2.1x_1^4+\frac{1}{3}x_1^6+x_1x_2-4x_2^2+4x_2^4$	$[-5,5]$	MN	−1.0316285
f_{17}	Branin	$f(x)=(x_2-\frac{5.1}{4\pi^2}x_1^2+\frac{5}{\pi}x_1-6)^2+10(1-\frac{1}{8\pi})\cos x_1+10$	$[-5,10]$ and $[0,15]$	MS	0.398
f_{18}	GoldStein-Price	$f(x)=[1+(x_1+x_2+1)^2(10-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)]$ $\times[30+(2x_1-3x_2^2)(18-32x_1+12x_1^2+48x_2-36x_1x_2+27x_2^2)]$	$[-2,2]$	MN	3
f_{19}	Shekel5	$f(x)=-\sum_{i=1}^{5}[(x-a_i)(x-a_i)^T+c_i]^{-1}$	$[0,10]$	MN	−10.1532
f_{20}	Shekel7	$f(x)=-\sum_{i=1}^{7}[(x-a_i)(x-a_i)^T+c_i]^{-1}$	$[0,10]$	MN	−10.4029
f_{21}	Shekel10	$f(x)=-\sum_{i=1}^{10}[(x-a_i)(x-a_i)^T+c_i]^{-1}$	$[0,10]$	MN	−10.5364

Table 2
Maximum generation number for benchmark functions.

Maximum number of generation	Benchmark functions
1500	$f_1, f_6, f_{10}, f_{12}, f_{13}$
2000	f_2, f_{11}
3000	f_7
4000	f_{15}
5000	f_4, f_5, f_9
9000	f_8
20,000	f_3
100	$f_{14}, f_{15}, f_{16}, f_{17}, f_{18}, f_{19}, f_{20}, f_{21}$

Steps	Drosophila based biological view	Population based algorithmic view
1	Initial location of food sources collected by olfactory receptors	Initialization of population V_{ij}, where $i = 1,2,\ldots,D$ and $j = 1,2,\ldots,P$ by using real parameter encoding systems
2	Evaluate concentration of ligands available in the food	Evaluate fitness of each individual in the populations
3	Select preferable food sources based on the concentration of ligand selected by external sensilla present in the proboscis	Use tournament selection
4	The sensory systems of Drosophila also try to evaluate the concentration of ligand in the neighborhood of food sources selected by external sensilla	The neighborhood search of each individual in the population is made by using Redundant Search (see Section 3.1)
5	After evaluating the concentration of ligands in Steps 3 and 4, the GPCR activates with best concentric ligand and generate signal to the SOG region of the brain and evaluation takes place. If the signal is more, then SOG region automatically provide positive signal to the proboscis to take food and which is treated as preferable best food	Select individuals for next population by using Eq. (3) (see Section 3.1)
6	Keep the preferable best food, the sensory organs tries to find out the improved concentric ligands among the preferable sources for binding with GPCR. Repeat Step 3–5	Memories the best string obtained so far. Repeat Step 3–5
7	If the ligand binding with GPCR is low, then a new food sources is generated in the neighborhood of preferable food sources or otherwise go to Step 9	If the fitness of any individuals in Step 6 with its old position in any iteration is within 1% radius, then apply mQA (see Section 3.2) or otherwise go to Step 9
8	If the concentration of the ligand in the new food source is more, then GPCR easily pass signal to bind with ligand and keep track as best food found so far i.e. Best food = max (ligand), otherwise go for next generation	The old individual will only retain its position if it is better than the current individual. Otherwise Gen = Gen + 1
9	If the best food found so far is acceptable or no food source is available, stop the process and returned the best food. Otherwise, go back to Step 3	Check for termination criterion (mentioned in Section 5.2). If the best value found so far is acceptable or if Gen = maximum number of generations, stop the process and returned the Best value. Otherwise, go back to Step 3

Table 3
Comparison of DFO with others in [31] for Series-1.

f	Dim.	DE	JDE	IMDE		DFO	DFO (QA)
				1st Process	2nd Process		
1	30	8.2E−14	1.1E−28	2.5E−32	2.1E−35	**2.20E−88**	**3.37e−115**
2	30	1.5E−9	1.0E−23	3.3E−23	1.7E−25	**2.64E−71**	**9.14e−72**
3	30	6.8E−11	3.1E−14	1.2E−24	7.8E−29	**0**[a]	1.40e−268
4	30	**0**	**0**	0.2E−3	3.4E−24	**0**	**0**
5	30	**0**	**0**	**0**	**0**	3.25E−03	0.96782
6	30	**0**	**0**	**0**	**0**	**0**	**0**
7	30	4.6E−3	3.15E−3	**2.4E−4**	3.4E−4	7.24E−03	8.91e−02
8	30	−11,080.1	**−12,569.5**	**−12,569.5**	**−12,569.5**	**−12569.5**	**−12569.5**
9	30	69.2	**0**	**0**	**0**	**0**	3.68e−17
10	30	9.7E−8	7.7E−15	4.9E−15	**4.6E−15**	8.32E−015	1.11e−14
11	30	**0**	**0**	**0**	**0**	**0**	4.33e−19
12	30	7.9E−15	6.6E−30	1.7E−32	1.6E−32	**1.57E−32**	1.62e−32
13	30	5.1E−14	5.0E−29	1.7E−32	1.3E−32	**1.49E−033**	1.40e−33
14	2	**0.998004**	**0.998004**	**0.998004**	**0.998004**	**0.998004**	**0.998004**
15	4	5.0E−4	4.0E−4	0.0003089	0.0003692	**0.0003075**	0.000395482
16	2	−1.03163	−1.03163	−1.03163	−1.03163	**−1.0316285**	**−1.03163**
17	2	**0.**397887	**0.397887**	**0.397887**	**0.397887**	**0.397887**	**0.397887**
18	2	**3**	**3**	**3**	**3**	**3**	**3**
19	2	**−10.1532**	**−10.1532**	**−10.1532**	**−10.1532**	−10.3012	−10.3012
20	2	**−10.4029**	**−10.4029**	**−10.4029**	**−10.4029**	−10.7708	−10.7708
21	2	**−10.5364**	**−10.5364**	**−10.5364**	**−10.5364**	−11.031	−11.031

[a] In referred paper [31], the value is obtained at generation: 20,000. However, in DFO it is reached at only 5000 generation.

The detailed mechanism (flow diagram) of the proposed DFO is sketched in Fig. 7.

5. Experimental study

This section represents the empirical evidence for the better performances of the proposed DFO over a number of existing evolutionary systems exist in the literature. In order to enumerate the performance of DFO, a set of benchmark problems has been used as test bed proposed by authors in [31], where they proposed IMDE. As reported in [31] that IMDE algorithm is superior to the DE, JDE, improved PSO, ABC and BSO techniques. For a fair observation to the performance of proposed DFO algorithm, three different series of test problems along with same stopping criteria quoted in [31] (as reported in Tables 1, 5 and 8) have been picked up in this paper. The proposed DFO algorithm simulation is coded in Dev C++ Pentium Dual Core 2.0 GHz machines with 1 GB RAM.

Table 4
Comparison of DFO with others in [31], for functions f_{19}, f_{20}, f_{21} of Series-1 of dimension 4.

f	Dim.	DE	JDE	IMDE		DFO	DFO (QA)
				1st process	2nd process		
19	4	−**10.1532**	−**10.1532**	−**10.1532**	−**10.1532**	−**10.1532**	−**10.1532**
20	4	−**10.4029**	−**10.4029**	−**10.4029**	−**10.4029**	−**10.4029**	−**10.4029**
21	4	−**10.5364**	−**10.5364**	−**10.5364**	−**10.5364**	−**10.5364**	−**10.5364**

Table 5
Benchmark functions – Series-2 (S: domain of the variables, f_{min}: global minima, C: function characteristics, U: unimodal, M: multimodal, S: separable, N: non-separable) taken from [31].

F	Function	Formulation	D	S	C	f_{min}
f_1	Sphere	$f(x) = \sum_{i=1}^{D} x_i^2$	10 and 30	$[-100, 100]$	US	0
f_2	Rosenbrock	$f(x) = \sum_{i=1}^{D-1}(100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2)$		$[-2.048, 2.048]$	UN	0
f_3	Schwefel 1.2	$f(x) = \sum_{i=1}^{D}(\sum_{j=1}^{i} X_i^2)$		$[-100, 100]$	UN	0
f_4	Schwefel	$f(x) = 418.9829 \times D - \sum_{i=1}^{D}(x_i \sin\sqrt{\lvert x_i \rvert})$		$[-500, 500]$	MS	0
f_5	Griewank	$f(x) = \sum_{i=1}^{D} \frac{x_i^2}{4000} - \prod_{i=1}^{D} \cos(\frac{x_i}{\sqrt{i}}) - 1$		$[-600, 600]$	MN	0
f_6	Weierstrass	$f(x) = \sum_{i=1}^{D}(\sum_{k=0}^{k_{max}}[a^k \cos(2\pi b^k(x_i + 0.5))]) - D\sum_{k=0}^{k_{max}}[a^k \cos(2\pi b^k(x_i + 0.5)]$ where $a = 0.5$, $b = 0.3$, $k_{max} = 20$		$[-0.5, 0.5]$	MN	0
f_7	Quartic	$f(x) = \sum_{i=1}^{D} i x_i^4 + random[0, 1)$		$[-1.28, 1.28]$	US	0
f_8	Non-continuous Rastrigin	$f(x) = \sum_{i=1}^{D}[y_i^2 - 10\cos(2\pi y_i) + 10]$ where $y_i = \begin{cases} x_i, \lvert x_i \rvert < \frac{1}{2} \\ \frac{rand(2x_i)}{2}, \lvert x_i \rvert \geqslant \frac{1}{2} \end{cases}$		$[-5.12, 5.12]$	MS	0
f_9	Rastrigin	$f(x) = 10D + \sum_{i=1}^{D}(x_i^2 - 10\cos(2\pi x_i))$		$[-5.12, 5.12]$	MS	0
f_{10}	Ackley	$f(x) = 20 + e - 20e^{-\left(\frac{1}{5}\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right)} - e^{-\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right)}$		$[-32.768, 32.768]$	MN	0

Table 6
Comparison of DFO with others in [31] for Series-2 for 10 dimension.

Method		Functions	1	2	3	4	5	6	7	8	9	10
FDR		Mean	5.99E−243	1.10E−3	8.44E−260	524	5.53E−02	**0**	4.75E−04	0.467	1.72	3.73E−15
		Best	4.69E−255	5.41E−5	1.47E−267	237	7.40E−03	**0**	1.07E−04	0	0	2.66E−15
CLPSO		Mean	3.98E−76	1.4	4.58E−76	**0**	1.53E−11	**0**	**7.05E−11**	**0**	**0**	2.66E−15
		Best	3.58E−78	1.16E−02	1.22E−78	**0**	**0**	**0**	3.37E−04	**0**	**0**	2.66E−15
CPSO-outer		Mean	**0**	0.266	**0**	521	**0**	**0**	1.99E−04	**0**	**0**	**0**
		Best	**0**	0	**0**	118	**0**	**0**	7.35E−06	**0**	**0**	**0**
IMDE	1st Process	Mean	**0**	2.835	6.40E−207	1.30E−04	**0**	**0**	3.90E−04	**0**	**0**	**5.90E−16**
		Best	**0**	0.0652	5.60E−210	1.30E−04	**0**	**0**	8.60E−06	**0**	**0**	**5.90E−16**
	2nd Process	Mean	**0**	**0**	4.70E−215	1.30E−04	**0**	**0**	1.50E−04	**0**	**0**	**5.90E−16**
		Best	**0**	**0**	1.20E−218	1.30E−04	**0**	**0**	3.10E−07	**0**	**0**	**5.90E−16**
DFO		Mean	**0**	4.90E−03	**0**	**1.27E−04**	**0**	**0**	1.32E−04	**0**	**0**	1.88E−15
		Best	**0**	3.57E−03	**0**	**1.27E−04**	**0**	**0**	1.72E−05	**0**	**0**	1.88E−15
DFO (QA)		Mean	**0**	8.18e−08	1.01e−283	1.29e−04	1.77e−15	**0**	7.42e−04	**0**	**0**	2.22e−15
		Best	**0**	4.89e−08	**0**	1.29e−04	8.88e−16	**0**	2.92e−04	**0**	**0**	1.26e−15

Table 7
Comparison of DFO with others in [31] for Series-2 for 30 dimension.

Method		Function->	1	2	3	4	5	6	7	8	9	10
FDR		Mean	5.84E−97	6.76	2.70E−93	3.27E+03	7.26E−02	0.32	3.28E−03	10.8	27.7	2.66E−14
		Best	1.41E−107	5.36	1.53E−103	2.76E+03	7.40E−03	7.11E−15	1.70E−03	7	20.9	2.04E−14
CLPSO		Mean	3.70E−22	1.83	3.41E−20	11.8	6.65E−11	**0**	5.44E−03	2.57E−02	2.12E−13	3.61E−12
		Best	3.27E−23	1.22	4.65E−21	0	0	**0**	2.51E−03	4.80E−13	1.07E−14	1.63E−12
CPSO-outer		Mean	9.48E−69	1.01	8.1E−52	1510	1.52E−02	1.91	1.50E−04	75.2	50	5.03E−15
		Best	0	1.05E−4	0	474	0	0.132	6.05E−05	25	0	0
IMDE	1st Process	Mean	3.20E−117	5.9E−31	7.80E−25	**3.80E−04**	**0**	**0**	1.90E−04	**0**	**0**	**4.10E−15**
		Best	9.1E−119	0	1.30E−26	**3.80E−04**	**0**	**0**	1.00E−05	**0**	**0**	**4.10E−15**
	2nd Process	Mean	3.60E−128	**0**	1.60E−28	**3.80E−04**	**0**	**0**	**1.50E−04**	**0**	**0**	**4.10E−15**
		Best	2.90E−129	**0**	8.70E−31	**3.80E−04**	**0**	**0**	**4.00E−06**	**0**	**0**	**4.10E−15**
DFO		Mean	**7.88E−201**	3.02E−03	**4.62E−84**	**3.80E−04**	**0**	**0**	1.23E−04	**0**	**0**	6.66E−15
		Best	**8.23E−311**	3.02E−03	**7.37E−296**	**3.80E−04**	**0**	**0**	2.18E−05	**0**	**0**	**2.96E−16**
DFO (QA)		Mean	**1.83e−222**	1.51	**1.20e−225**	3.81e−04	4.33e−19	8.52e−15	9.29e−03	2.31e−18	2.42e−18	8.88e15
		Best	**2.31e−312**	1.20e−01	2.98e−259	3.81e−04	2.62e−19	**0**	6.22e−04	8.67e−19	1.73e−18	1.33e−15

5.1. Test bed

A set of 21 classical benchmark test functions from [31] is reconsidered in this experiment to evaluate the performance of DFO. Based on their properties, the functions may be divided into three groups: functions with no local minima, many local minima and a few local minima. The analytical form of these function are given in Table 1. The first seven functions f_1–f_7 are high dimensional uni-modal functions. Functions f_8–f_{13} are high dimensional multi-modal functions with many local minima and highly non-linear in nature. The number of local minima's of these function increases exponentially with increase of dimension. The remaining functions f_{14}–f_{21} are low-dimensional functions with a smaller number of local minima.

5.2. Results and discussion

In [31], authors presented their results in three different tables according to the fixation of maximum number of generation to stop run. They are listed below in the name of Series 1, 2 and 3.

(i) For Series 1: Maximum generations vary for different functions (reported in Table 2).
(ii) For Series 2: Maximum number of generations = 5000.
(iii) For Series 3: Maximum number of generations = 5000, 7500 and 10,000 for 10, 20 and 30 dimensions for function from f1 to f5, respectively. But for function f6, the maximum number of generation taken is equal to 2000, as mentioned in [31].

In this present study, all the above three series are considered. Like in [31], the population size is fixed at 100 and average of best objective function value in 50 independent runs for each function is recorded in the corresponding tables. The series wise results and discussion is presented below. It is worth to note for further study that

DFO: DFO where mQA is used.
DFO (QA): DFO where QA is used.

5.2.1. Comparison of DFO with IMDE, DE, JDE and DFO(QA)(for Series 1)

Considering the problem Series-1 (in Table 1), the minimum objective function values of all 21 classical test functions are reported in Table 3 along with the results as quoted in [31]. Better values are highlighted with bold face in Table 3.

It is observed from the results (in Table 3) that DFO performed better than IMDE, JDE and DE on an average. For uni-modal functions f_1–f_2, DFO is better than IMDE, JDE and DE. For functions f_3–f_4, DFO reached the global optimum, while IMDE did not and for function f_5, DFO not able to reach global optimum, while IMDE did it. For function f_6, all the algorithms reached the global optimum and for function f_7, the performance of 1st Process of IMDE is better than DFO.

For multi-modal functions, f_8, f_9 and f_{11}, all the algorithms reached the global optimum. But for function f_{10} IMDE performs better than DFO. For functions f_{12} and f_{13}, DFO performs better than all other algorithms. For the low-dimensional functions f_{14}–f_{18}, all the algorithms reached the global optimum except for f_{15} where, IMDE, DE, JDE not able to reached the global optimum.

In [31], authors solved f_{19}–f_{21}, for problem dimension 2. But in many papers [6,32,33], those problems are solved for 4 or more dimensions. In this paper, the result by DFO for f_{19}–f_{21} is recorded both for 2 dimensions (Table 3) and 4 dimensions (Table 4). Clearly, it is observed from those tables that DFO fails to beat IMDE, DE and JDE for dimension 2, whereas DFO outperforms for dimension 4. It is also observed that DFO outperforms DFO (QA) in most of the cases. Better values are highlighted with bold face in Table 4.

Therefore, in general proposed DFO algorithm performs better than the IMDE, DE, JDE and DFO (QA).

5.2.2. Comparison of DFO algorithm with IMDE and improved PSO algorithms (for Series 2)

Considering the problem Series-2 (in Table 5), the minimum objective function values of all 10 classical test functions are reported in Tables 6 and 7 along with the results as quoted in [31] for 10 and 30 dimension, respectively. The author in [31],

Table 8
Benchmark functions – Series-3 (S: domain of the variables, $f_{\min}$: global minima, C: function characteristics, U: unimodal, M: multimodal, S: separable, N: non-separable) taken from [31].

f	Function	Formulation	S	C	$f_{\min}$
f_1	Sphere	$f(x) = \sum_{i=1}^{D} x_i^2$	$[-100, 100]$	US	0
f_2	Rosenbrock	$f(x) = \sum_{i=1}^{D-1} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2)$	$[-30, 30]$	UN	0
f_3	Rastrigin	$f(x) = 10D + \sum_{i=1}^{D} (x_i^2 - 10\cos(2\pi x_i))$	$[-5.12, 5.12]$	MS	0
f_4	Ackley	$f(x) = 20 + e - 20e^{-\left(\frac{1}{5}\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right)} - e^{-\left(\frac{i}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right)}$	$[-30, 30]$	MN	0
f_5	Griewank	$f(x) = \sum_{i=1}^{D} \frac{x_i^2}{4000} - \prod_{i=1}^{D} \cos\left(\frac{x_i}{\sqrt{i}}\right) - 1$	$[-600, 600]$	MN	0
f_6	Schaffer	$f(x) = 0.5 + \left(\frac{(\sin\sqrt{\sum_{i=1}^{D} x_i^2})^2 - 0.5}{(1 + 0.001(\sum_{i=1}^{D} x_1^2 + x_2^2))^2}\right)$	$[-100, 100]$	MN	0

Table 9
Comparison of DFO with others in [31] for Series-3 for 10, 20 and 30 dimension.

Function->			f_1			f_2			f_3			f_4			f_5		f_6	
Method		Dim->	10	20	30	10	20	30	10	20	30	10	20	30	10	20	30	2
ABC		Mean	4.9E−28	3.1E−25	6.4E−24	9.3E−03	1.3E−02	3.4E−02	4.4E−24	2.0E−22	8.6E−22	3.2E + 00	1.8E + 00	9.8E−01	8.5E−05	6.4E−04	1.4E−03	9.4E−08
		Stdv	2.2E−25	5.4E−23	1.2E−22	1.1E−02	7.3E−02	4.8E−02	6.2E−23	7.0E−21	5.3E−21	6.9E−04	1.7E−07	3.0E−08	9.3E−12	1.0E−12	2.8E−12	3.2E−14
BSO-RPTVW		Mean	1.7E−118	7.2E−114	3.2E−111	1.9E−09	9.0E−09	6.0E−08	8.6E−93	6.9E−−91	2.6E−86	**8.0E−53**	**6.8E−53**	**5.7E−54**	1.8E−20	9.7E−20	2.4E−19	3.5E−56
		Stdv	7.4E−118	1.5E−113	6.7E−111	3.2E−08	1.5E−07	4.4E−06	4.8E−92	3.1E−90	7.3E−−86	**3.9E−52**	**4.7E−52**	**2.2E−53**	7.3E−19	3.1E−19	5.2E−17	6.5E−56
IMDE	1st Process	Mean	**0**	2.1E−267	7.2E−238	**0**	**0**	**0**	**0**	**0**	**0**	**5.9E−16**	4.1E−15	4.1E−15	**0**	**0**	**0**	2.9E−03
		Stdv	**0**	4.9E−267	1.3E−237	**0**	**0**	**0**	**0**	**0**	**0**	**0**	0	0	**0**	**0**	**0**	3.3E−03
	1st Process	Mean	**0**	**0**	6.2E−296	**0**	**0**	**0**	**0**	**0**	**0**	**5.9E−16**	4.1E−15	4.1E−15	**0**	**0**	**0**	5.0E−03
		Stdv	**0**	**0**	1.6E−295	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	5.5E−03
DFO		Mean	**0**	**0**	**0**	4.90E−03	7.04E−03	3.11E−03	**0**	**0**	**0**	1.88E−15	5.77E−15	7.91E−15	**0**	**0**	**0**	**0**
		Stdv	**0**	**0**	**0**	1.43E−03	2.52E−03	1.25E−03	**0**	**0**	**0**	7.92E−16	1.29E−15	1.10E−15	**0**	**0**	**0**	**0**
DFO (QA)		Mean	**0**	2.58e−182	5.74e−252	8.18e−08	4.99e−05	1.28e−03	**0**	8.6e−19	2.3e−18	2.22e−15	7.54e−15	1.55e−14	1.4e−19	2.68e−19	8.13e−19	**0**
		Stdv	**0**	1.62e−180	1.399e−250	1.89e−08	2.13e−05	1.25e−03	**0**	9.5e−19	1.6e−18	1.20e−15	1.08e−15	2.36e−15	5.4e−20	0	1.79e−19	**0**

compare IMDE with several improved PSO namely FDR, CLPSO and CPSO-outer respectively. Best values are highlighted with bold face in Tables 6 and 7.

It is observed from the result in Table 6 that DFO performs better than IMDE, FDR, CLPSO and CPSO-outer. For functions f_4, DFO performs better than all the three algorithms and for functions f_1, f_3, f_5, f_6, f_8 and f_9, DFO and CPSO-outer reached the global optima along with IMDE, but for function f_3 where IMDE not able to reach the global optima. For functions f_2 and f_{10}, both IMDE and CPSO-outer performs better than DFO and for function f_7, CLPSO performs better than the all other algorithms. It is also seen that DFO outperforms DFO (QA) in most of the cases.

The experimental results of Series-2 for functions with 30 dimensions are reported in Table 7. For functions f_1 and f_3, DFO performs better than IMDE, CLSPO, CPSO-outer and for functions f_5, f_6, f_8 and f_9, DFO, IMDE and CPSO-outer reached the global optima. For functions f_2 and f_{10}, IMDE performs better than DFO and for function f_4, both IMDE and DFO algorithms shown equal value. For function f_7, 2nd Process of IMDE performs better than DFO. It is also seen that DFO outperforms DFO (QA) in most of the cases.

From the results in Table 7, it is observed that DFO performs better than all other algorithms for solving high dimension problems. Thus, based on the above results, it can be concluded that DFO algorithm is dependable for solving high dimensional optimization functions.

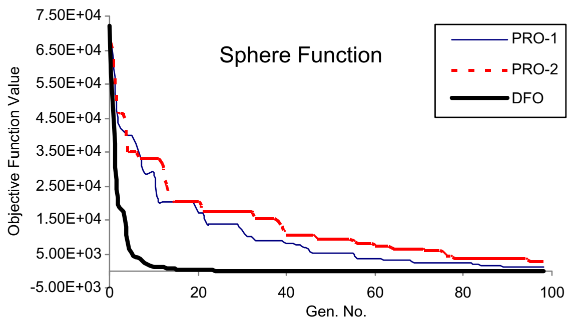

Fig. 8a. Convergence for test function f_1.

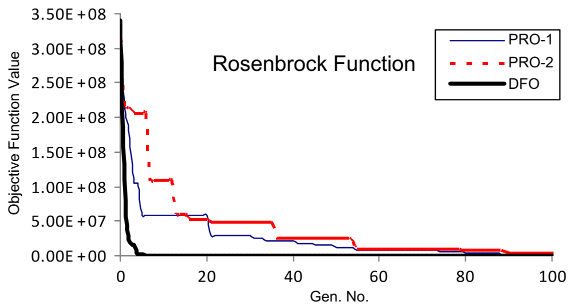

Fig. 8b. Convergence for test function f_5.

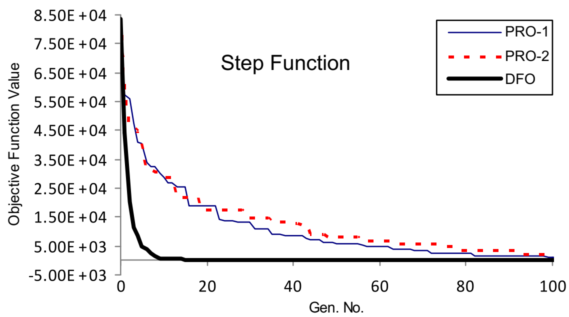

Fig. 8c. Convergence for test function f_6.

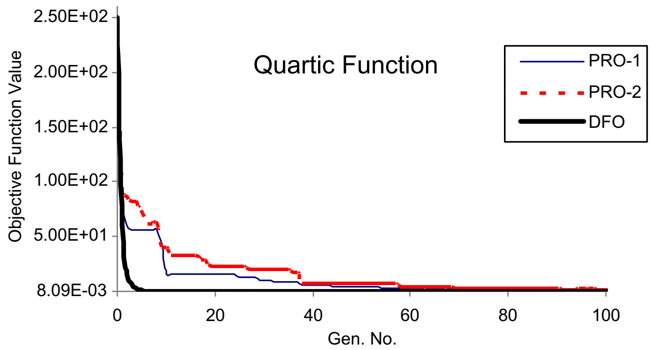

Fig. 8d. Convergence for test function f_7.

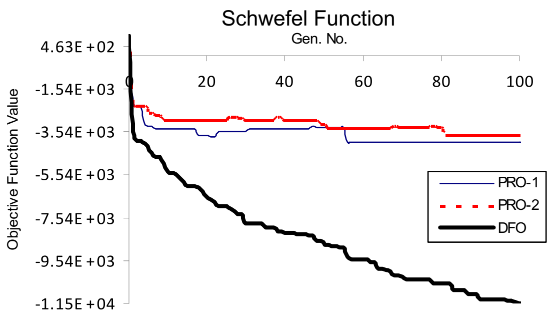

Fig. 8e. Convergence for test function f_8.

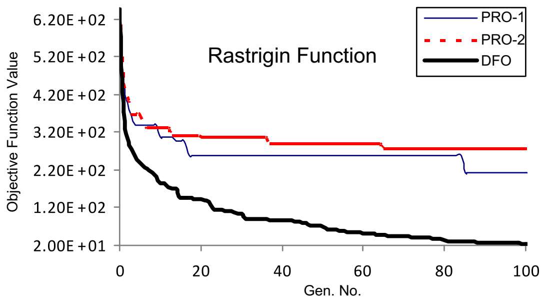

Fig. 8f. Convergence for test function f_9.

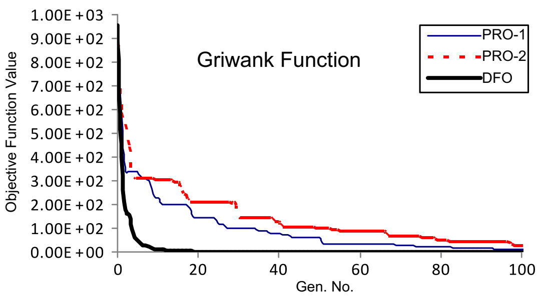

Fig. 8g. Convergence for test function f_{11}.

Table 10
Performance of DFO with DE, GSA and DE-GSA to solve Gas Transmission Compressor Design.

Item	DE	GSA	DE-GSA	DFO	DFO (QA)	Beightler and Phillips [37]
X_1	52.3966	53.0547	53.5080	**53.4831**	53.4961	55
X_2	1.1875	1.1919	1.1901	**1.19011**	1.1901	1.195
X_3	24.6697	24.5070	24.7624	**24.715**	24.7149	25.026
$f(X)$	2.96443E+06	2.96449E+06	2.96437E+06	**2.96291E+06**	2.9631E+06	2.96455E+06

Table 11
Performance of DFO with DE, GSA and DE-GSA to solve Optimal Capacity of Gas production facilities.

Item	DE	GSA	DE-GSA	DFO	DFO (QA)	Beightler and Phillips [37]
X_1	**17.5**	**17.5**	**17.5**	**17.5**	**17.5**	17.5
X_2	**600**	**600**	**600**	**600**	**600**	465
$f(X)$	**169.844**	**169.844**	**169.844**	**169.844**	**169.844**	173.76

5.2.3. Comparison of DFO algorithm with IMDE, improved ABC & BSO (for Series 3)

Considering the problem Series-3 (in Table 8), the minimum objective function values of all 6 classical test functions are reported in Table 9 along with the results as quoted in [31] for 10, 20 and 30 dimensions, respectively. The author in [31], compare IMDE with several improved ABC and BSO-RPTVW. Best values are highlighted with bold face in Table 9.

From Table 9, for functions f_1, f_3, f_5 and f_6, it is seen that DFO reached the global optima but for functions f_2, IMDE performs better than DFO. Also, for function f_4, BSO-RPTVW performs better than all other algorithms. It is worth to note that DFO outperforms DFO (QA) in most of the cases.

In order to evaluate the rate of convergence of DFO, a set of seven typical test functions ($f_1, f_5, f_6, f_7, f_8, f_9$ and f_{11}) are considered arbitrarily. All test functions starts with same initial population for fair comparison of DFO with IMDE. To avoid complication in convergence graph, only the best methods of [31] i.e. both the process of IMDE (namely PRO-1 and PRO-2) is picked. All the seven functions are shown in Figs. 8a–8g. It is clear from Figs. 8a–8g that DFO converge faster than both the process within a few generations only.

6. Real life problems

In this section two real life problems are taken from [35] for evaluating the performance of proposed DFO with DE, GSA and DE-GDS. They are as follows:

RP1: Gas Transmission Compressor Design and
RP2: Optimal Capacity of Gas production facilities.

The minimum objective function values for RP1 and RP2 are reported in Tables 10 and 11, respectively along with results quoted in [35]. Best values are highlighted with bold face in Tables 10 and 11.

It is observed from Table 10 that the proposed DFO gives better function value than DE, GSA, DE-GSA, DFO (QA) and the result quoted in [37] for RP1. However, for RP2 DFO performs equally well with DE, GSA, DFO (QA) and DE-GSA; but yields better function value than that in [37]. Hence, from the above, it is to be concluded that the performance of DFO is better than all reported algorithms in [35] and [37]. Also, DFO performs better than DFO with QA.

7. Conclusion

In spite of a number of meta-heuristics available in literature, an effort is made in this paper to enhance further the quality of exploration and exploitation mechanism over the search space. A new an efficient algorithm called Drosophila Food-Search Optimization (DFO) is proposed, which is based on the food-search behavior of a fly in nature namely *D. Melanogaster*. After the experimental study and from the numerical results it is concluded that the proposed DFO overtakes many recent popular meta-heuristics like DE, JDE, IMDE, CLPSO, CPSO-outer, ABC and BSO algorithm. DFO also performs better with modified QA rather than DFO with simple QA. It works better even in solving real world problem too. Further by the convergence graph, the faster convergence rate of DFO is concluded. Future research may be carried out by employing DFO in solving complex real problems even for constrained optimization.

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