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Owl search algorithm: A novel nature-inspired heuristic paradigm for global optimization

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Abstract. This paper presents, a novel nature-inspired optimization paradigm, named as owl search algorithm (OSA) for solving global optimization problems. The OSA is a population based technique based on the hunting mechanism of the owls in dark. The proposed method is validated on commonly used benchmark problems in the field of optimization. The results obtained by OSA are compared with the results of six state-of-the-art optimization algorithms. Simulation results reveal that OSA provides promising results as compared to the existing optimization algorithms. Moreover, to show the efficacy of the proposed OSA, it is used to design two degree of freedom PI (OSA-2PI) controller for temperature control of a real-time heat flow experiment (HFE). Experimental results demonstrate that OSA-2PI controller is more precise for temperature control of HFE in comparison to the conventional PI controller.

Keywords: Nature-inspired algorithm, unconstrained optimization, two degree of freedom PI controller, Heat flow experiment

1. Introduction

In recent years, metaheuristic optimization techniques have gained significant attention of researchers due to successful application of these techniques in a variety of complex optimization problems. These techniques are found more effective than conventional methods which use derivative information of function. Two eminent features of any metaheuristic technique are exploration and exploitation [1]. Exploration phase of algorithm, also known as diversification, redirects the search towards unvisited regions of the search space, in order to find new but potentially better solutions. On the other hand, exploitation or intensification phase helps the algorithm to search in the neighbourhood of current best solutions. There are distinct objectives behind the development of modern metaheuristics such as fast and effortless handling of complex as well as large problems and designing more effective and robust techniques [2].

There is no limitation on the source of motivation to design a metaheuristic technique. As an illustration, the gravitational search algorithm (GSA) is inspired from law of gravitation and mass interaction [3], interior search algorithm (ISA) is based on the concepts of interior designing and decoration [4] etc. Nevertheless, nature is always a primary source of motivation for proposing new metaheuristic techniques. A brief literature review of nature-inspired optimization algorithms is presented in Table 1. Various nature-inspired optimization algorithms are available in literature, however “no free lunch (NFL)” theorem [19] supports the present study as proposed

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Table 1
Brief literature review of nature-inspired optimization algorithms

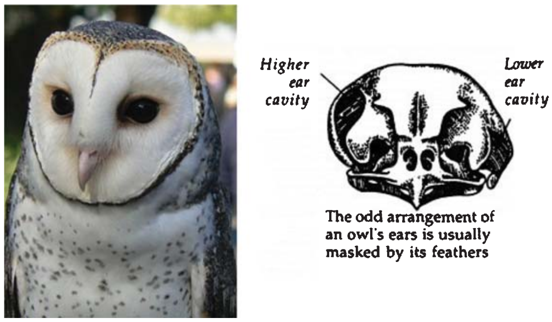
Algorithm	Inspiration	Year
Genetic algorithm (GA) [5]	Evolution	1975
Particle swarm optimization (PSO) [6]	Bird flock	1995
Ant colony optimization (ACO) [7]	Ant colony	2006
Artificial bee colony (ABC) [8]	Honey bee	2006
Monkey search (MS) [9]	Monkey climbing process on trees while looking for food	2007
Firefly algorithm (FFA) [10]	Social behavior of fireflies	2009
Bat algorithm (BA) [11]	Echolocation behaviour of bats	2010
Krill herd (KH) [12]	Herding behavior of krill individuals in nature	2012
Dolphin echolocation (DE) [13]	Echolocation ability of dolphins	2013
Lightning search algorithm (LSA) [14]	Natural phenomenon of lightning	2015
Dragonfly algorithm (DA) [15]	Static and dynamic swarming behaviours of dragonflies	2015
Multi-verse optimizer (MVO) [16]	Basic concepts in cosmology	2016
Shark smell optimization (SSO) [17]	Ability of shark in finding its prey by smell sense	2016
Whale optimization algorithm (WOA) [1]	Social behavior of humpback whales	2016
Crow search algorithm (CSA) [18]	Intelligent food hiding behaviour of crows	2016

algorithm may outperform other existing optimizers on some problems. This paper introduces a new simple, easy to implement and powerful nature-inspired optimization algorithm called as owl search algorithm (OSA). This algorithm simulates the hunting mechanism of barn owls which rely on their hearing capability to find prey (vole) in the dark night rather than sight. The effectiveness of OSA is validated on a set of unconstrained numerical benchmark functions. The results obtained are compared with standard optimizers like GA, PSO, BA, FFA, MVO, and KH. Further suitability of proposed technique, to resolve real world black box optimization problems, is investigated by conducting a real-time experimental study on Heat Flow Experiment (HFE) setup.

The rest of the paper is structured as follows: Section 2 briefly outlines the motivation of proposed work. Section 3 presents the implementation of OSA. Sections 4 and 5 present the comparative analysis of results on standard benchmark functions and real-time Heat Flow Experiment respectively. Finally, the work is concluded in Section 6.

2. Inspiration

Owls are typically nocturnal but highly efficient predators with an extraordinary auditory system which helps to locate the prey (vole). Some of the species like barn owls (Fig. 1a) have evolved with a distinct anatomical feature of auditory system with vertical asymmetry of ears (Fig. 1b) [20]. Due to this unique feature, the sound reaches one ear before the other, and location of prey is obtained. Hence prey can be located in dark by hearing ability instead



(a) Real barn owl (b) Barn owl's skull

Fig. 1. Real barn owl and its anatomy of ears.

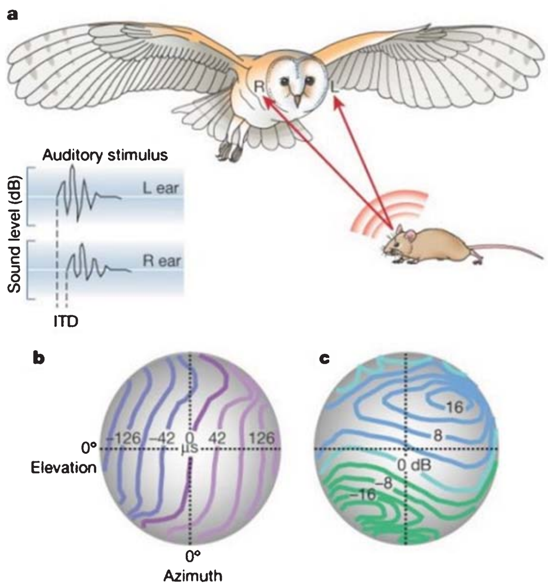


Fig. 2. Auditory map of prey sound generated by owl's brain.

of sight [21]. The sound signal generated by a vole (Fig. 2a) is processed in the owl's brain in two parts i.e. the interaural time difference (ITD), and interaural level (loudness) difference (ILD) (Fig. 2b) to prepare an auditory map (Fig. 2c) of prey location [20]. The distance of prey is estimated on the basis of time and intensity differences of sound wave arrival [22].

3. Owl search algorithm (OSA)

Similar to other nature-inspired population based algorithms, OSA starts the optimization process with an initial set of random solutions which represent the initial position of owls in a forest (d dimensional search space). If there exist n number of owls in a forest, then their random position is stored in a $n \times d$ matrix as follows:

$$O = \begin{bmatrix} O_{1,1} & O_{1,2} & \cdots & \cdots & O_{1,d} \\ O_{2,1} & O_{2,2} & \cdots & \cdots & O_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ O_{n,1} & O_{n,2} & \cdots & \cdots & O_{n,d} \end{bmatrix} \quad (1)$$

where matrix element $O_{i,j}$ represents the j^{th} variable (dimension) of i^{th} owl. A uniform distribution (Equation (2)) is used to allocate the initial location of each owl in the forest.

$$O_i = O_L + U(0, 1) \times (O_U - O_L) \quad (2)$$

where O_L and O_U are lower and upper bounds respectively of i^{th} owl O_i in j^{th} dimension and $U(0, 1)$ is a uniformly distributed random number in the range [0,1]. The fitness of each owl's location in a forest is evaluated using an objective function and stored in the following matrix:

$$f = \begin{bmatrix} f_1\left(\left[O_{1,1}, O_{1,2}, \ldots, O_{1,d}\right]\right) \\ f_2\left(\left[O_{2,1}, O_{2,2}, \ldots, O_{2,d}\right]\right) \\ \vdots \\ \vdots \\ f_n\left(\left[O_{n,1}, O_{n,2}, \ldots, O_{n,d}\right]\right) \end{bmatrix} \quad (3)$$

In the present work, it is assumed that fitness value of each owl's position directly relates the intensity information received through ears. Thus best owl receives max intensity (for maximization problems) as it is more close to vole. The normalized intensity information of i^{th} owl is utilized to update the position and may be calculated as:

$$I_i = \frac{f_i - w}{b - w} \quad (4)$$

where

$$b = \max_{k \in 1,\ldots,n} f_k \quad (5)$$

$$w = \min_{k \in 1,\ldots,n} f_k \quad (6)$$

The distance information of each owl and prey is calculated by the following equation:

$$R_i = \| O_i, V \|_2 \quad (7)$$

where V is the location of prey which is achieved by the fittest owl. It is also assumed that there exists only one vole (global optimum) in the forest. Owls take silent flights while moving towards the prey. Hence, they receive changed intensity obeying the inverse square law of sound intensity (Fig. 3) [23]. The change in intensity for i^{th} owl can be obtained as follows:

$$Ic_i = \frac{I_i}{R_i^2} + Random\ noise \quad (8)$$

In Equation (8), R_i^2 is used instead of $4\pi R_i^2$ and random noise of environment is also considered to make the mathematical model more realistic. In the real world, voles are active and hence their movement forces the owls to change their current position silently. In the present work, the movement of prey is designed using probability and hence new positions of owls can be obtained by following position updating mechanism:

$$O_i^{t+1} = \begin{cases} O_i^t + \beta \times Ic_i \times |\alpha V - O_i^t|, & \text{if} p_{vm} < 0.5 \\ O_i^t - \beta \times Ic_i \times |\alpha V - O_i^t|, & \text{if} p_{vm} \geq 0.5 \end{cases} \quad (9)$$

where p_{vm} is the probability of vole movement, α is a uniformly distributed random number in the range [0, 0.5] and β is a linearly decreasing constant from 1.9 to 0. β introduces large changes initially and promotes the exploration of search space. As the algorithm progresses these variations are reduced to encourage exploitation. The proposed method has only one user defined parameter (i.e β) whereas GA, PSO, BA etc. have large number of parametric settings.

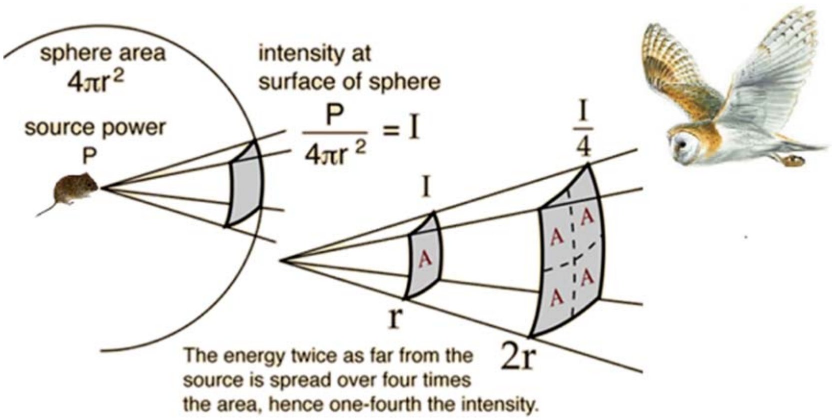


Fig. 3. Inverse square law of sound intensity.

4. Experimental validation

In this section, two experimental studies are carried out to examine the efficiency, effectiveness and stability of OSA. The first one is a simulation study conducted on ten benchmark problems and the results are compared statistically with six state-of-the-art optimization algorithms. The second study is hardware validation on a real-time engineering design problem.

4.1. Experimental study on benchmark problems

In this experimental study, a benchmark suit of ten standard functions [24] are considered to validate the performance of OSA. This suit includes unimodal, multimodal and high-dimensional benchmark functions. For impartial evaluation, common parameters of all the algorithms like problem dimensions, population size and maximum number of function evaluations are considered to be the same. The standard parametric settings of algorithms are used as given in Table 2. A valid statistical analysis is performed by independently executing each algorithm for 30 trial runs for each benchmark function with maximum 30000 number of function evaluations in each run. The recorded results are presented in Table 3 in terms of their best, worst, mean value and standard deviation (SD). It is revealed from the results that OSA outperforms all the other six algorithms in all cases except for function TF3. In case of TF3, none of the algorithms could find global optimum solution but MVO shows better performance in terms of accuracy. For function TF7 most of the algorithms could find

Table 2
Parametric settings of algorithms

Name of Parameter	GA	PSO	BA	FFA	MVO	KH	OSA
Crossover fraction	0.8	-	-	-	-	-	-
Selection	Tournament	-	-	-	-	-	-
Crossover	Arithmetic	-	-	-	-	-	-
Mutation	Adaptive feasible	-	-	-	-	-	-
c1 and c2	-	2	-	-	-	-	-
Inertia weight	-	0.9	-	-	-	-	-
Loudness	-	-	0.5	-	-	-	-
Pulse rate	-	-	0.5	-	-	-	-
f_{min}, f_{max}	-	-	0, 2	-	-	-	-
α	-	-	-	0.25	-	-	-
β	-	-	-	0.20	-	-	-
γ	-	-	-	1	-	-	-
WEP_{max}, WEP_{min}	-	-	-	-	1, 0.2	-	-
V_f	-	-	-	-	-	0.02	-
D_{max}	-	-	-	-	-	0.005	-
N_{max}	-	-	-	-	-	0.01	-
β (linearly varying)	-	-	-	-	-	-	1.9-0

Table 3
Statistical results acquired from GA, PSO, BA, FFA, MVO, KH and OSA after 30 independent runs on benchmark functions

Function		GA	PSO	BA	FFA	MVO	KH	OSA
TF1	Best	3.9630E+06	4.8215E+08	2.3094E+10	2.0214E+03	1.2844E+05	4.2321E+03	**8.1166E-60**
	Worst	5.7634E+06	5.7003E+09	6.9382E+10	1.2078E+04	5.0108E+05	2.4338E+05	**3.4006E-43**
	Mean	4.9323E+06	1.9034E+09	3.8444E+10	4.7586E+03	2.7324E+05	7.5525E+04	**1.1361E-44**
	SD	4.4253E+05	1.2098E+09	1.3038E+10	2.6260E+03	8.6995E+04	4.6589E+04	**6.2081E-44**
TF2	Best	4.7694E+00	1.4694E+04	4.0951E+04	1.4656E+04	9.2006E+01	9.8984E+03	**1.0584E-64**
	Worst	5.2668E+03	7.9058E+04	5.7355E+07	3.8679E+04	3.1523E+02	7.1154E+04	**4.1172E-52**
	Mean	5.7329E+02	3.4275E+04	2.5257E+06	2.6443E+04	1.9133E+02	3.1796E+04	**2.2816E-53**
	SD	1.1980E+03	1.7105E+04	1.0560E+07	6.6120E+03	6.4489E+01	1.7799E+04	**7.5801E-53**
TF3	Best	1.1848E+00	6.3753E+02	1.8503E+04	3.0471E-01	**2.4877E-01**	2.7577E-01	4.8354E-01
	Worst	1.7022E+00	4.5505E+03	7.0283E+04	1.0157E+00	1.3518E+00	1.0163E+00	5.0000E-01
	Mean	1.4350E+00	2.0341E+03	3.8745E+04	4.0939E-01	5.2591E-01	5.6240E-01	4.9895E-01
	SD	1.2544E-01	8.5452E+02	1.1319E+04	1.5596E-01	2.9414E-01	2.5248E-01	3.4469E-03
TF4	Best	2.6786E+00	8.6492E+00	1.7202E+01	7.7087E-03	1.4773E-01	1.5744E-02	**8.8818E-16**
	Worst	3.6454E+00	1.6029E+01	1.9967E+01	2.0154E-02	2.7439E+00	3.2869E+00	**8.8818E-16**
	Mean	3.3673E+00	1.1121E+01	1.9791E+01	1.3591E-02	1.1877E+00	1.8294E+00	**8.8818E-16**
	SD	1.8638E-01	1.5605E+00	6.5680E-01	2.6408E-03	7.2758E-01	6.2898E-01	**0.0000E+00**
TF5	Best	1.6724E-01	9.9499E+00	1.9501E+02	2.4279E-03	3.1657E-01	1.1253E-02	**0.0000E+00**
	Worst	2.9838E-01	4.2255E+01	6.8387E+02	5.9629E-03	7.3709E-01	2.6511E-01	**0.0000E+00**
	Mean	2.4063E-01	2.1289E+01	3.9058E+02	3.9206E-03	5.3260E-01	4.1584E-02	**0.0000E+00**
	SD	3.3169E-02	7.4842E+00	1.1472E+02	9.7419E-04	1.1226E-01	5.0919E-02	**0.0000E+00**
TF6	Best	3.9371E+00	9.0796E+02	1.8201E+04	1.5287E-03	1.5467E-01	1.2141E-02	**5.9501E-71**
	Worst	6.2102E+00	4.2463E+03	6.9138E+04	6.1995E-03	5.7240E-01	1.0634E+00	**2.9808E-50**
	Mean	5.2432E+00	2.1438E+03	3.8109E+04	3.0050E-03	3.2357E-01	1.6247E-01	**1.0209E-51**
	SD	5.7999E-01	8.6931E+02	1.1135E+04	1.0807E-03	9.2028E-02	2.0769E-01	**5.4376E-51**
TF7	Best	**0.0000E+00**	1.0000E+00	5.5040E+03	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Worst	2.0000E+00	1.9100E+02	1.9767E+04	1.0000E+00	2.0000E+00	**0.0000E+00**	**0.0000E+00**
	Mean	7.0000E-01	3.7367E+01	1.0845E+04	6.6667E-02	4.0000E-01	**0.0000E+00**	**0.0000E+00**
	SD	7.0221E-01	5.1696E+01	3.6443E+03	2.5371E-01	6.2146E-01	**0.0000E+00**	**0.0000E+00**
TF8	Best	1.0753E-02	6.3034E-01	6.4342E+00	1.8480E-03	5.7964E-03	1.3555E-05	**3.0545E-47**
	Worst	2.1415E+00	4.3929E+00	6.1320E+01	4.3026E-03	3.9335E-02	3.4228E-04	**5.5052E-29**
	Mean	8.1023E-01	2.4909E+00	2.9075E+01	2.6360E-03	2.0507E-02	1.3219E-04	**2.3856E-30**
	SD	5.6240E-01	1.0203E+00	1.2909E+01	5.6867E-04	7.7546E-03	9.7199E-05	**1.0376E-29**
TF9	Best	3.1326E-06	1.1657E+00	1.1656E+01	5.2233E-07	5.6727E-05	3.1980E-03	**4.0810E-96**
	Worst	1.0842E-01	3.6964E+01	2.9962E+02	2.5962E-06	1.0868E-03	3.2933E+00	**5.2759E-77**
	Mean	9.1356E-03	7.2906E+00	9.3712E+01	1.3848E-06	2.0769E-04	5.2154E-01	**1.7823E-78**
	SD	2.4277E-02	7.3451E+00	8.1922E+01	5.6504E-07	1.8630E-04	7.1552E-01	**9.6285E-78**
TF10	Best	1.3771E-06	4.1380E-03	3.4819E+00	3.2766E-06	2.0994E-05	5.1153E-07	**5.9484E-104**
	Worst	6.2299E-02	4.4955E+00	2.9347E+02	1.1025E-05	1.0418E-03	1.9172E-04	**2.1009E-85**
	Mean	4.3179E-03	4.8335E-01	1.1247E+02	5.8596E-06	3.0326E-04	2.0596E-05	**1.4572E-86**
	SD	1.3160E-02	8.6825E-01	6.6985E+01	1.9157E-06	2.1765E-04	3.6555E-05	**4.8716E-86**

global optimum solutions but the performance of both KH and OSA are found better. Thus it is revealed that the performance of the proposed technique is quite accurate. However, apart from accuracy, an optimization algorithm must have fast convergence rate with sufficient amount of stability to get the global optimum results. Therefore convergence rate analysis and ANOVA test are performed and few results are presented in Fig. 4. It is clear from the results that the proposed method offers very fast convergence rate. Moreover, the results of ANOVA test for OSA are also found satisfactory as 25^{th} and 75^{th} percentiles of the samples decline toward the global optimum solution with a narrow interquartile range. Quantitative analysis (Table 3) also confirms the stable performance of OSA as the value of SD is very low.

In spite of the statistical analysis, two algorithms may perform equally well with no significant difference in their results. Several non-parametric statistical tests discussed in literature [25] may be performed to differentiate their performance. In this study, most frequently used Wilcoxon's test is employed to find the difference in significance level of two algorithms. To conduct this test, best results on the benchmark problems for 30 independent runs of an algorithm are considered and the level of significance is considered to be 95% ($\alpha = 0.05$). Table 4 shows the recorded results of Wilcoxon's test where '+' sign indicates that the proposed algorithm performed significantly better than the compared algorithm. On the other hand, '$-$' sign indicates that the proposed algorithm is inferior to the compared technique. It is

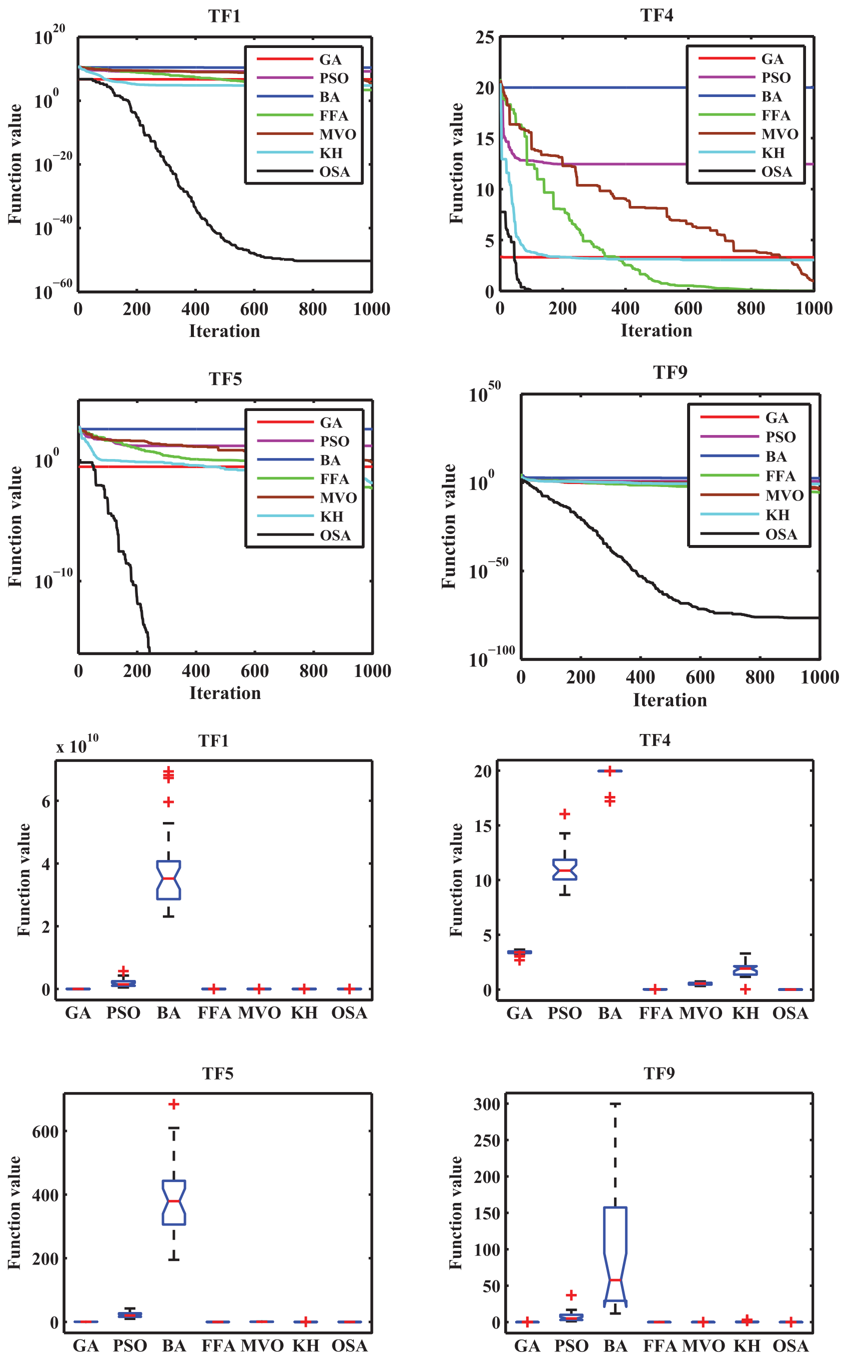


Fig. 4. Convergence rate comparison and results of ANOVA for benchmark functions TF1, TF4, TF5 and TF9.

revealed from Table 4 that OSA is found significantly better in comparison to other existing optimizers as higher number of '+' counts are recorded. Next section presents the hardware validation of the proposed technique while solving a real-time controller design problem in process industry.

5. Real-time experimental validation

Recently nature-inspired algorithms are widely used in solving real-world problems. Therefore, to show the applicability of proposed technique, it is used to design two degree of freedom proportional

Table 4
Results of Wilcoxon's test for OSA against other six algorithms for each benchmark function with 30 independent runs (α = 0.05)

Function	GA vs OSA		PSO vs OSA		BA vs OSA		FFA vs OSA		MVO vs OSA		KH vs OSA	
	p-value	win	p-value	win	p-value	win	p-value	win	p-value	win	p-value	win
TF1	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+
TF2	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+
TF3	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	3.1767E-06	+	3.5062E-05	+	7.7200E-02	–
TF4	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+
TF5	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+
TF6	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+
TF7	6.1856E-07	+	1.6911E-17	+	1.6911E-17	+	4.9150E-01	–	7.9701E-04	+	1.0000E-00	–
TF8	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+
TF9	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+
TF10	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+	1.6911E-17	+
+/-		10/0		10/0		10/0		10/1		10/0		10/2

Fig. 5. Heat Flow Experiment (HFE).

integral (2-DOF PI) controller for precise temperature control of a real-time Heat Flow Experiment (HFE). HFE is made up of a fiberglass chamber fitted with blower and coil based heater at one end followed by three equally spaced temperature sensors with the other end open (Fig. 5). A tachometer is placed on the blower to measure the speed of fan. Temperature inside the chamber is measured at three distinct locations by platinum temperature transducers. Two analog input voltage signals called as heater voltage (V_h) and blower voltage (V_b), are generated, and applied to HFE through data acquisition (DAQ) device to control the heater temperature and blower speed respectively. The temperature inside the chamber changes with the change in two input voltage signals and this change is measured by three temperature sensors. The output signal of sensors can be accessed from three analog input channels of the DAQ device. The range of input voltage signals (V_h & V_b) is from 0V to 5V only. As the plant is in direct interaction with the surroundings, it becomes crucial to control its temperature in precise manner. Hence, the temperature of chamber at any sensor i can be described as follows:

$$\frac{d}{dt}T_i(t) = f(V_h, V_b, T_a, x_i) \qquad i = 1, 2, 3 \tag{10}$$

where T_a is the ambient temperature and x_i is the distance of i^{th} sensor from the heater. In this experimental study, voltage of the heater V_h is manipulated

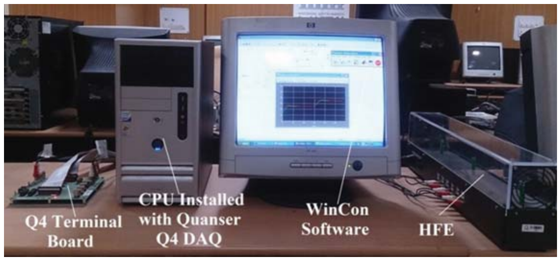


Fig. 6. Laboratory set up of HFE.

to control temperature profile of the duct, while the blower voltage V_b is maintained at 5V to have a uniform temperature profile. Figure 6 shows the snapshot of actual experimental setup of HFE, used in this work. The HFE apparatus is interfaced to personal computer with WinCon 5.2 software, which operates the plant in real-time in MATLAB Simulink environment. MATLAB R2007a is configured with Real-Time workshop (RTW) and Microsoft Visual C++ is used as compiler.

As discussed previously, HFE apparatus is in direct interaction with the surroundings i.e. ambient temperature is a potential source of disturbance. Therefore, to get a precise temperature control with such a plant, 1-DOF control scheme i.e. conventional PI controller is not worthwhile. This motivates for the use of 2-DOF control scheme [26, 27] for HFE. The basic block diagram of the implemented control scheme is shown in Fig. 7. The control signal u_c generated by the 2-DOF PI controller can be defined in s-domain as follows [26]:

$$\begin{aligned} u_c(s) &= K_p\left[\beta r(s) - Y_{out}(s) + \frac{1}{T_i s}\{r(s) - Y_{out}(s)\}\right] \\ &= K_p\{\beta r(s) - Y_{out}(s)\} + \frac{K_i}{s}\{r(s) - Y_{out}(s)\} \end{aligned} \tag{11}$$

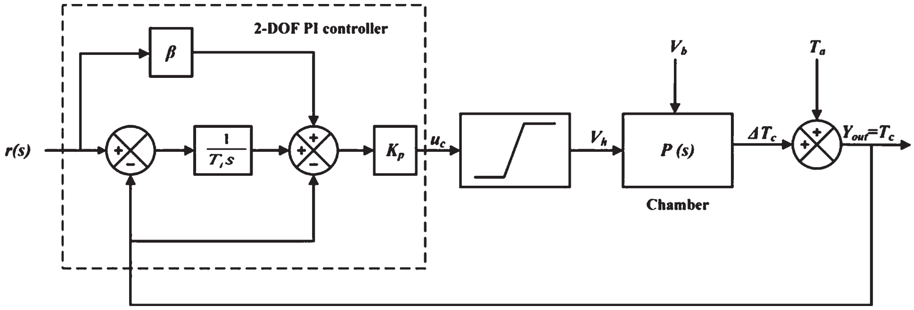


Fig. 7. Block diagram of 2-DOF PI based temperature control of HFE.

The control signal after passing through limiter, is given as voltage input to the heater and hence controls the temperature of HFE. The voltage input to the blower and ambient temperature are constant during the experimentation. It is clear from Equation (11) that in order to generate a precise control signal, appropriate values of controller parameters such as K_p, K_i and β are required. In the present study, a novel method for controller tuning is proposed in which OSA heuristically optimizes the tuning parameters of 2-DOF PI controller, which leads to OSA-2PI controller. OSA is used offline on the following identified plant model of HFE:

$$P(s) = \frac{-0.2405s + 1.721}{s^2 + 1.17s + 0.2} \tag{12}$$

by satisfying the following performance criterion:

$$J = w_1 IAE + w_2 Os \tag{13}$$

where IAE is Integral Absolute Error and Os is the percentage overshoot of the response. w_1 and w_2 are the weighing factors obtained after rigorous experimentation having values 0.10 and 0.90 respectively. Fig. 8 shows the convergence plot of OSA for the above defined performance criterion and the optimal combination of controller parameters are $K_p = 0.6982$, $K_i = 0.0725$ and $\beta = 0.9993$. It is revealed from Fig. 8 that the convergence rate of OSA is fast enough for solving black box optimization problem with unknown search space. The experimental results of OSA-2PI controller are compared for set point tracking against Tyreus-Luyben tuned PI (TL-PI) controller. It is revealed from the results (Fig. 9) that OSA-2PI controller controls temperature of HFE more precisely in comparison to conventionally tuned PI controller. This is due to the reason that proposed controller makes precise variations in the control signal (Fig. 10) due to appropriate tuning parameters. The quantitative analysis of the results on the basis of IAE (Fig. 11) supports the same. Thus OSA-2PI is far better than TL-PI controller for sharp and precise temperature control of HFE. It is revealed from the experimental studies that OSA provides optimal solutions with higher accuracy and fast convergence rate.

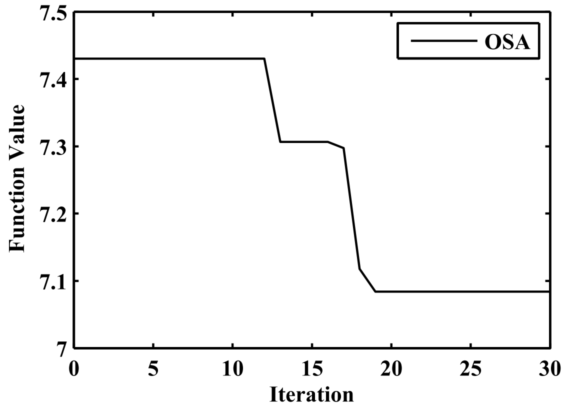


Fig. 8. Convergence plot of OSA for performance criterion J.

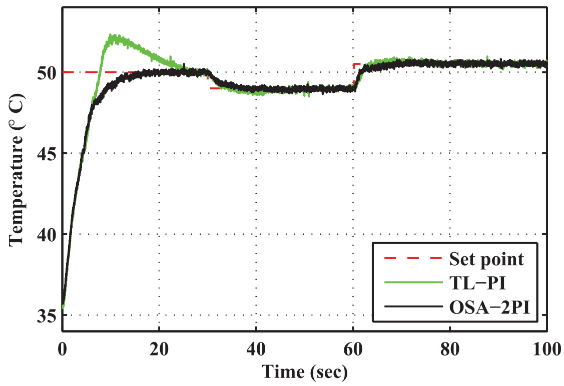


Fig. 9. Temperature variations of HFE controlled by the designed controllers for set point tracking.

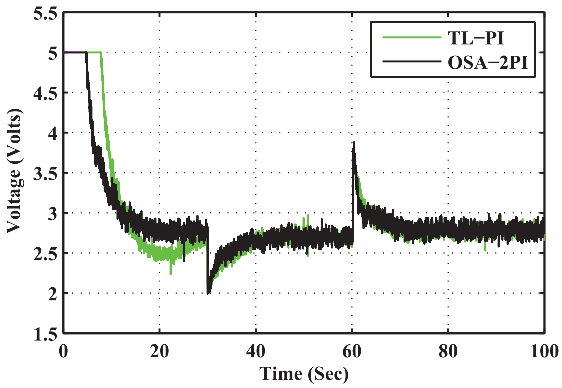


Fig. 10. Control effort applied by designed controllers for set point tracking.

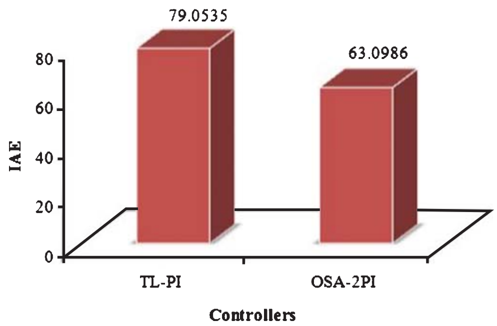


Fig. 11. IAE comparison of designed controllers for set point tracking.

6. Conclusion

The present work proposes a novel nature-inspired algorithm, called as OSA which is a population based technique imitates the hunting mechanism of the owls in complete darkness. The proposed method is first validated on benchmark functions and the results obtained are compared with the results of various existing optimization algorithms. It is revealed from the simulation results that the proposed OSA provides more accurate and stable optimization solutions as compared to other algorithms. Moreover, to show the effectiveness of the proposed technique, it is applied in designing of two degree of freedom PI (OSA-2PI) controller for temperature control of a real-time HFE. It is revealed from experimental results that the OSA-2PI controller is more precise for temperature control of HFE in comparison to conventional PI controller. Therefore, the proposed algorithm can be further tested to solve other complex black box optimization problems.

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