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A new bio-inspired optimisation algorithm: Bird Swarm Algorithm

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A new bio-inspired algorithm, namely Bird Swarm Algorithm (BSA), is proposed for solving optimisation applications. BSA is based on the swarm intelligence extracted from the social behaviours and social interactions in bird swarms. Birds mainly have three kinds of behaviours: foraging behaviour, vigilance behaviour and flight behaviour. Birds may forage for food and escape from the predators by the social interactions to obtain a high chance of survival. By modelling these social behaviours, social interactions and the related swarm intelligence, four search strategies associated with five simplified rules are formulated in BSA. Simulations and comparisons based on eighteen benchmark problems demonstrate the effectiveness, superiority and stability of BSA. Some proposals for future research about BSA are also discussed.

Keywords: bird swarms; swarm intelligence; social behaviours; social interactions; Bird Swarm Algorithm; optimisation

1. Introduction

Optimisation problems abound in the real world. There are many different optimisation problems, which are continuous, discrete, linear, nonlinear, non-smooth or non-convex. The continuously differentiable problems can be attacked by the traditional methods, such as gradient-based methods. If the problems are very complex, such as non-convex or non-differentiable, they may not be efficiently solved by some traditional methods. Despite there being still several methods that can deal with some complex problems, they may not get optimal results in reasonable computational effort. For example, the NP problems cannot be solved by traditional methods in an affordable time.

Meta-heuristic methods come into being as an alternative to the traditional optimisation methods. With their merits of finding acceptable solutions in an affordable time and being tolerant of non-convex and non-differentiable, nature-inspired meta-heuristic algorithms have attracted great research interest during the recent years.

Nature has been providing unlimited inspiration for human to learn and design new meta-heuristic algorithms. Inspired by the abstraction of the natural evolution and selection of biological systems, GA (Kuo & Lin, 2013), DE (Das & Suganthan, 2011), Cultural Algorithm (Jin, 2001), Mimetic Algorithm (Smith, 2007), etc. were proposed. PSO (Rezaee Jordehi &

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Jasni, 2013), Ant Colony Optimization (Dorigo & Stutzle, 2004), Artificial Fish Swarm Algorithm (Gao, Wu, Zenger, & Huang, 2010), Artificial Bee Colony (Karaboga & Basturk, 2007), Glowworm Swarm Optimization (Krishnanand & Ghose, 2009), Cuckoo Search (Yang & Deb, 2014), Bat Algorithm (Yang, 2010), Krill Herd (Gandomi & Alavi, 2012), etc. were inspired by the swarm intelligence of social animals. Inspired by the plant, Invasive Weed Optimization (Mehrabian & Lucas, 2006) and Flower Pollination Algorithm (Yang, Karamanoglu, & He, 2014) were designed. Harmony Search (Manjarres et al., 2013), Charged System Search (Kaveh & Talatahari, 2010), Brain Storm Optimization (Shi, 2011), etc. were inspired by physical principles and nature phenomena.

Though many algorithms were developed to deal with optimisation applications, there still exists no universal algorithm. Thus, the research of finding more efficient algorithms is still in progress.

In this paper, a new bio-inspired algorithm, namely Bird Swarm Algorithm (BSA), is proposed as a new optimisation method. BSA is simplification of the social behaviours and social interactions in bird swarms. It mimics the birds' foraging behaviour, vigilance behaviour and flight behaviour. Thus, the swarm intelligence can be efficiently extracted from the bird swarms to optimise problems.

The rest of the paper is organised as follows. Section 2 illustrates the details of BSA. Simulations and comparisons are presented in Section 3. Finally, some conclusions and discussions are given in Section 4.

2. The Bird Swarm Algorithm

2.1 Biological fundamentals

Many bird species are gregarious, such as finches. They may roost communally, forage and fly in flocks (Anderson, 2006). These behaviours are considered as emergent behaviours arising from simple rules such as separation, alignment and cohesion. Through the simplest social interaction, the swarm behaviours can develop complex motions and interactions.

Foraging in flocks, birds may get more information than their own senses can gather, and have survival advantage and good foraging efficiency. If one bird finds some food patches, others may feed from them (Kennedy, Eberhart, & Shi, 2001). While foraging, birds often aggregate in response to predation threat (Krause & Ruxton, 2002). They frequently raise their heads and scan their surroundings. These behaviours, interpreted as vigilance behaviour (Anderson, 2006), may be conducive to detecting predators (Lima & Dill, 1990). Studies showed that birds would randomly choose between foraging and keeping vigilance (Bednekoff & Lima, 1998). Birds often give alarm calls when they detect a predator (Pulliam, Pyke, Caraco, & Pulliam, 1982). Thus, the whole group would fly off together. It can reasonably conclude that birds in a flock have a better chance of detecting a potential threat than a single one. A reduction in individual vigilance with an increase in group size is so widespread in many birds (Ekman, 1987; Elgar & Catterall, 1981; Sullivan, 1984). In other words, a bird can spend more time foraging as group size increases without affecting the increased risk of being attacked by the predator (Beauchamp, 1998; Roberts, 2003).

The birds on the periphery of a group have more chance of being attacked by the predators than those in the centre. Studies suggested that animals foraging in the centre of flock may move to their neighbours to protect themselves from being attacked by the predators (Pulliam, 1973). Each bird would try to move towards the centre of the flock as they perceive it. This motion, however, may be affected by the interference induced by competing among the bird swarms (Beauchamp, 2003). Thus, birds may not directly move towards the centre of the swarm.

Birds obviously would fly to another site for foraging or just for escaping from predators. After they arrive at a new site, they would search for food again. It is usually observed that there exist producers and scroungers in flock-feeding birds. Producers actively search for food, while scroungers just feed from the food found by the producers (Barnard & Sibly, 1981; Giraldeau & Caraco, 2000). Individuals usually use alternative behavioural strategies, and choose between producing and scrounging (Liker & Barta, 2002; Coolen, Giraldeau, & Lavoie, 2001; Johnson, Giraldeau, & Grant, 2001; Koops & Giraldeau, 1996). Studies suggested that the birds with low reserves will often be scroungers, while the ones with high reserves would be the producers (Barta & Giraldeau, 2000).

For flock-feeding birds, the social behaviours give the social animals a survival advantage (Sirot, 2006). Each bird can benefit from the social interactions to achieve the optimal survival and good foraging efficiency. The essence behind the social behaviours and the social interactions is the swarm intelligence, which can be associated with designing a new optimisation method to optimise the objective problems.

2.2 Bird Swarm Algorithm theory

The aforementioned social behaviours can be simplified by some idealised rules as follows.

(1) Each bird can switch between the vigilance behaviour and foraging behaviour. Whether bird forages or keeps vigilance is modelled as a stochastic decision (Rule 1).

(2) While foraging, each bird can promptly record and update its previous best experience and the swarms' previous best experience about food patch. This experience can also be used to search for food. Social information is shared instantaneously among the whole swarm (Rule 2).

(3) When keeping vigilance, each bird would try to move towards the centre of the swarm. This behaviour can be affected by the interference induced by the competition among swarm. The birds with the higher reserves would be more likely to lie closer to the centre of the swarm than those with the lower reserves (Rule 3).

(4) Birds would periodically fly to another site. When flying to another site, birds may often switch between producing and scrounging. The bird with the highest reserves would be a producer, while the one with the lowest reserves would be a scrounger. Other birds with reserves between the highest and lowest reserves would randomly choose to be producer and scrounger (Rule 4).

(5) Producers actively search for food. Scroungers would randomly follow a producer to search for food (Rule 5).

Given these rules formulated verbally, the new meta-heuristic algorithm by precise mathematical model can be developed. The basic flowchart of the BSA is shown in Figure 1.

All N virtual birds, depicted by their position x_i^t ($i \in [1, \ldots, N]$) at time step t, forage for food and fly in a D-dimensional space.

2.2.1 Foraging behaviour

Each bird searches for food according to its experience and the swarms' experience. Rule 2 can be written mathematically as follows:

$$x_{i,j}^{t+1} = x_{i,j}^t + \left(p_{i,j} - x_{i,j}^t\right) \times C \times \mathrm{rand}(0,1) + \left(g_j - x_{i,j}^t\right) \times S \times \mathrm{rand}(0,1), \tag{1}$$

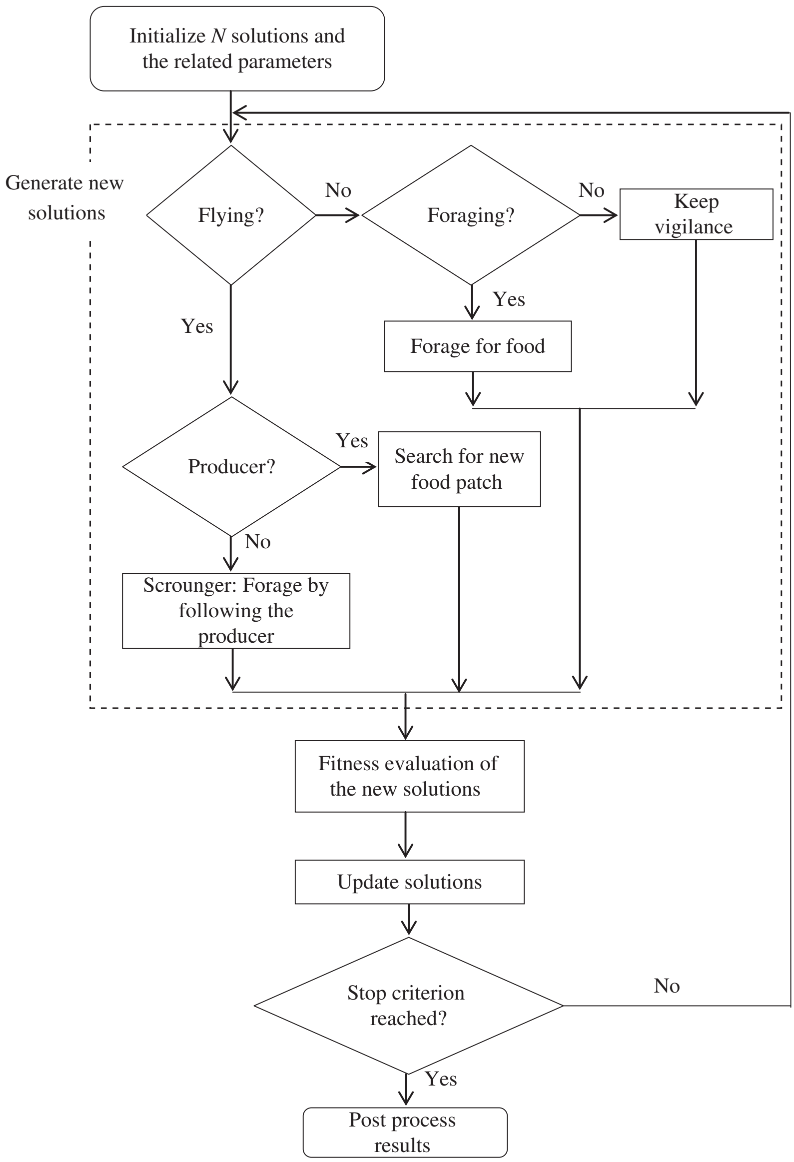

Figure 1. Basic flowchart of BSA.

where $j \in [1, \ldots, D]$, rand (0, 1) denotes independent uniformly distributed numbers in (0, 1). C and S are two positive numbers, which can be respectively called as cognitive and social accelerated coefficients. $p_{i,j}$ is the best previous position of the ith bird and g_j the best previous position shared by the swarm.

For simplicity, the Rule 1 can be formulated as a stochastic decision. If a uniform random number in (0, 1) is smaller than $P\,(P \in (0, 1))$, a constant value, the bird would forage for food. Otherwise, the bird would continue vigilance.

2.2.2 Vigilance behaviour

Given the Rule 3, birds would try to move to the centre of the swarm, and they would inevitably compete with each other. Thus, each bird would not directly move towards the centre of the swarm. These motions can be formulated as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + A1\left(\mathrm{mean}_j - x_{i,j}^{t}\right) \times \mathrm{rand}(0,\ 1) + A2\left(p_{k,j} - x_{i,j}^{t}\right) \times \mathrm{rand}(-1, 1), \tag{2}$$

$$A1 = a1 \times \exp\left(-\frac{p\mathrm{Fit}_i}{\mathrm{sumFit} + \varepsilon} \times N \right), \tag{3}$$

$$A2 = a2 \times \exp\left(\left(\frac{p\mathrm{Fit}_i - p\mathrm{Fit}_k}{|p\mathrm{Fit}_k - p\mathrm{Fit}_i| + \varepsilon} \right) \frac{N \times pFit_k}{\mathrm{sumFit} + \varepsilon} \right) \tag{4}$$

where $k\,(k \neq i)$ is a positive integer, which is randomly chosen between 1 and N. $a1$ and $a2$ are two positive constants in [0, 2], $p\mathrm{Fit}_i$ denotes the ith bird's best fitness value and sumFit represents the sum of the swarms' best fitness value. ε, which is used to avoid zero-division error, is the smallest constant in the computer. mean_j denotes the jth element of the average position of the whole swarm.

When a bird moves towards the centre of the swarm, it will inevitably compete with each other. For simplicity, the average fitness value of the swarm is considered as the indirect effect induced by the surroundings when a bird moves to the centre of the swarm. Given the fact that each bird wants to stand at the centre of swarm, the product of $A1$ and rand(0,1) should not be more than 1. Here, $A2$ is used to simulate the direct effect induced by a specific interference when a bird moves to the centre of the swarm. If the best fitness value of a random kth bird $(k \neq i)$ is better than that of the ith bird, then $A2 > a2$, which means that the ith bird may suffer a greater interference than the kth bird. Though there are some randomness and unpredictability, the kth bird would be more likely to move towards the centre of the swarm than the ith bird. In this paper, it solves the minimal optimisation problems, unless otherwise indicated. Thus, the smaller the fitness value is, the better the fitness value will be.

2.2.3 Flight behaviour

Birds may fly to another site in response to predation threat, foraging or any other reasons. When arrived at a new site, they would forage for food again. Some birds acting as producers would search for food patches, while others try to feed from the food patch found by the producers. The producers and scroungers can be separated from the swarm according to Rule 4. The behaviours of the producers and scroungers can be described mathematically as follows, respectively:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \mathrm{rand}n(0, 1) \times x_{i,j}^{t}, \tag{5}$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \left(x_{k,j}^{t} - x_{i,j}^{t}\right) \times FL \times \mathrm{rand}(0, 1), \tag{6}$$

where rand$n$(0,1) denotes Gaussian distributed random number with mean 0 and standard deviation 1, $k \in [1, 2, 3, \ldots N]$, $k \neq i$. $FL(FL \in [0, 2])$ means that the scrounger would follow the producer to search for food.

For simplicity, we assume that each bird flies to another place every FQ unit interval. Here, FQ is a positive integer.

2.2.4 *The computational procedure and computational complexity of BSA*

Based on the aforementioned descriptions, BSA can be summarised as the pseudo code shown in Table 1.

The computational complexity of BSA can be estimated. According to Figure 1 and Table 1, the procedures of generating, evaluating and updating new solutions need the highest computational overhead of executing BSA. The computational complexities of other steps are rather simple, and can be neglected. Thus the 'worst-case' complexities can be computed by considering the procedures of generating, evaluating and updating new solutions.

The time complexity of generating, evaluating and updating new solutions is the same, namely $O(MN)$. To summarise, the overall computational complexity of the BSA is $O(MN)$.

3. Validation and comparison

In this section, 18 benchmark problems (shown in Table 2) (Yang, 2014) are optimised to investigate the effectiveness, efficiency and stability of BSA. These problems contain unimodal, multi-modal, high-dimensional and low-dimensional cases. The formulae of BSA reveal a natural relationship between BSA, and PSO and DE. Moreover, PSO and DE are two famous meta-heuristic algorithms; thus, the two algorithms will be used as the comparison algorithms. In all case studies, the statistical results would be used to investigate the BSA's superiority by

Table 1. Pseudo code of BSA.

Bird Swarm Algorithm (BSA)
Input: N: the number of individuals (birds) contained by the population
    M: the maximum number of iteration
    FQ: the frequency of birds' flight behaviours
    P: the probability of foraging for food
    C, S, $a1$, $a2$, FL: five constant parameters
$t = 0$; Initialise the population and define the related parameters
Evaluate the N individuals' fitness value, and find the best solution
While ($t < M$)
  If (t % $FQ \neq 0$)
    For $i = 1$: N
      If rand(0,1) $< P$
        Birds forage for food (Equation 1)
      Else
        Birds keep vigilance (Equation 2)
      End if End for
  Else
    Divide the swarm into two parts: producers and scroungers.
    For $i = 1$: N
      If i is a producer
        Producing (Equation 5)
        Else
        Scrounging (Equation 6)
      End if End for
  End if Evaluate new solutions
  If the new solutions are better than their previous ones, update them
  Find the current best solution
$t = t + 1$; End while
Output: the individual with the best objective function value in the population

Table 2. Benchmark problems.

Problem	Bounds	Optimum
$F1 = \sum_{i=1}^{20} x_i^2$	[− 100,100]	0
$F2 = \sum_{i=1}^{20}\left(\sum_{j=1}^{i} x_j\right)^2$	[− 100,100]	0
$F3 = \max_i\{\lvert x_i\rvert,\ 1 \le i \le 20\}$	[− 100,100]	0
$F4 = \sum_{i=1}^{20} \lvert x_i\rvert + \prod_{i=1}^{20}\lvert x_i\rvert$	[− 10,10]	0
$F5 = \sum_{i=1}^{20}(\lfloor x_i + 0.5\rfloor)^2$	[− 100,100]	0
$F6 = \sum_{i=1}^{20}\lvert x_i\rvert^{i+1}$	[− 1,1]	0
$F7 = \sum_{i=1}^{20} x_i^2 + \left(\sum_{i=1}^{20} 0.5ix_i\right)^2 + \left(\sum_{i=1}^{20} 0.5ix_i\right)^4$	[− 5,10]	0
$F8 = \sum_{i=1}^{20}(i\,x_i^2)$	[− 5.12, 5.12]	0
$F9 = \sum_{i=1}^{20}(x_i^2 - 10\cos(2\pi x_i) + 10)$	[− 5.12, 5.12]	0
$F10 = -20\exp(-0.2\sqrt{\frac{1}{20}\sum_{i=1}^{20} x_i^2} - \exp\left(\frac{1}{20}\sum_{i=1}^{20}\cos\left(2\pi x_i^2\right)\right) + 20 + \mathrm{e}$	[− 32, 32]	0
$F11 = \frac{1}{4000}\sum_{i=1}^{20} x_i^2 - \prod_{i=1}^{20}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	[− 600, 600]	0
$F12 = x\sin\sqrt{\lvert y+1-x\rvert}\cos\sqrt{\lvert y+1+x\rvert} + (y+1)\cos\sqrt{\lvert y+1-x\rvert}\sin\sqrt{\lvert y+1+x\rvert}$	[− 512, 512]	− 511.7
$F13 = -\left(\frac{3}{0.05+(x^2+y^2)}\right)^2 - (x^2+y^2)^2$	[− 5.12, 5.12]	− 3600
$F14 = 0.5{*}(x^4 + y^4 - 16{*}(x^2+y^2) + 5{*}(x+y))$	[− 5, 5]	− 78.3323
$F15 = 0.26\left(x_1^2 + x_2^2\right) - 0.48x_1x_2$	[− 10, 10]	0
$F16 = (1.5 - x_1 + x_1x_2)^2 + (2.25 - x_1 + x_1x_2^2)^2 + (2.625 - x_1 + x_1x_2^3)^2$	[− 4.5, 4.5]	0
$F17 = 1 + \sin^2(x_1) + \sin^2(x_2) - 0.1\mathrm{e}^{-(x_1^2+x_2^2)}$	[− 10, 10]	0.9
$F18 = \sum_{i=1}^{5}[i\cos((i-1)x+i)]\sum_{j=1}^{5}\left[j\cos((j+1)y+j)\right] + (x+1.42513)^2 + (y+0.80032)^2$	[− 10, 10]	− 176.1375

comparing with PSO and DE. For a fair comparison, all of the parameters of these methods, such as the population size, maximum number of iterations, etc., are set to be the same. The population size is 6 times and 5 times the specific dimension of $F1 - F11$ and $F12 - F18$, respectively. All algorithms would run 100 independent trials with 1000 iterations. All the experiments using Visual Studio 2010 are performed on a computer with 3.2 GHz quad-core processor and 2.0 GB of RAM in Windows 7 operating system. The related parameter values of each algorithm are given in Table 3.

According to the statistic results given in Table 4, it is obvious that BSA is superior to PSO and DE. PSO and DE may trap into local optima for solving $F2$, $F9$, $F12$, $F13$, $F14$, $F16$, $F17$ and $F18$. DE may also be susceptible to premature convergence when solving $F3$ and $F10$. As for the accuracy and stability, BSA can yield more accurate and stable results than those of PSO and DE for solving all the problems except $F5$, which can be solved by these three algorithms with the comparable precision.

The trade-off between accuracy and convergence time of these three algorithms are presented in Figure 2. Compared with the results of PSO and DE for solving $F1$, $F2$, $F3$, $F5$, $F7$–$F11$ and $F13$, BSA can significantly improve convergence speed and reduce calculation amount without affecting the accuracy of the results. BSA can also yield comparable convergence performance with PSO and DE for solving the other problems except $F12$. The convergence performance of BSA for solving $F12$ is slightly worse than those of PSO and DE.

Having analysed the details about PSO and DE, it can be concluded that time complexity of PSO and DE is the same as that of BSA. The theoretical time complexity of these three algorithms is $O(MN)$.

Based on the comparison results given in Table 4 and Figure 2, it can be reasonably concluded that the performance of the BSA outperforms that of PSO and DE in terms of optimisation accuracy, efficiency, stability and convergence performance.

The superiority of BSA over PSO and DE should be the case. In fact, PSO and the mutation operator of DE are the special cases of the BSA under appropriate simplifications. The formula describing the birds' foraging behaviour in BSA is similar to that of PSO. If we set FQ as an infinite number and $P = 1$, BSA essentially becomes the standard PSO. Moreover, the formula representing the scroungers' behaviours in BSA corresponds to the mutation operator in DE. Besides possessing the merits of PSO and DE, BSA has its own distinguishing features. BSA has four different search strategies and can flexibly adjust the different search strategies, thus making BSA strike better balance between exploration and exploitation than PSO and DE.

4. Conclusions and discussions

Imitating the best feature in nature to solve optimisation problems is an ongoing work. In the present work, Bird Swarm Algorithm, inspired from the bird swarms, is proposed as a new method for solving optimisation applications. Birds mainly have three kinds of behaviours, including foraging behaviour, vigilance behaviour and flight behaviour, and can obtain a

Table 3. The parameter values of the three algorithms.

Algorithm	Parameter values
PSO	$c1 = c2 = 1.49445$, $w = 0.729$
DE	$\mathrm{CR} = 0.9$, $F = 0.6$
BSA	$C = S = 1.5$,$a1 = a2 = 1$, $P \in [0.8,1]$, $FL \in [0.5,0.9]$, $FQ = 3$

Table 4. Comparison of statistical results obtained by BSA, PSO and DE.

Problem	Algorithm	Best	Mean	Worst	SD
*F*1	PSO	0	0	0	1.8988e − 35
	BSA	0	0	0	0
	DE	0	0	0	1.94304e − 12
*F*2	PSO	191.61632	1181.68129	4637.12542	81.9389
	BSA	0	0	0	0
	DE	14.57637	147.07872	555.31305	10.5381
*F*3	PSO	0	1.6e − 7	1.41e − 6	2.31673e − 8
	BSA	0	0	0	1.91005e − 130
	DE	0.00375	3.08942	30.27557	0.430579
*F*4	PSO	0	0	0	1.10567e − 20
	BSA	0	0	0	8.78619e − 133
	DE	4.3e − 7	2.57e − 6	4.075e − 5	4.32847e − 7
*F*5	PSO	0	0	0	0
	BSA	0	0	0	0
	DE	0	0	0	0
*F*6	PSO	0	0	0	4.78569e − 60
	BSA	0	0	0	0
	DE	0	0	0	0
*F*7	PSO	0	0	0	6.58358e − 11
	BSA	0	0	0	0
	DE	0.00001	0.00013	0.00156	2.03004e − 5
*F*8	PSO	0	0	0	2.13096e − 37
	BSA	0	0	0	0
	DE	0	0	0	4.15726e − 14
*F*9	PSO	10.94454	21.26284	41.78822	0.600484
	BSA	0	0	0	0
	DE	8.41884	22.70527	43.97510	0.706925
*F*10	PSO	0	0	0	1.31168e − 16
	BSA	0	0	0	0
	DE	0	0.35702	11.64977	0.170962
*F*11	PSO	0	5e − 8	5.34e − 6	5.36538e − 8
	BSA	0	0	0	0
	DE	0	0	0	1.05399e − 12
*F*12	PSO	−511.70773	−504.67360	−456.50873	0.917353
	BSA	−511.70773	−511.56605	−510.08006	0.047209
	DE	−511.70773	−508.77971	−440.30385	0.923235
*F*13	PSO	−3600	−2884.94048	−2748.78234	31.5129
	BSA	−3600	−3600	−3600	0
	DE	−2748.782	−2748.782	−2748.782	4.59341e − 13
*F*14	PSO	−78.33233	−77.20139	−64.19561	0.387394
	BSA	−78.33230	−78.33230	−78.33210	4.44555e − 6
	DE	−78.33230	−77.91132	−64.19561	0.216586
*F*15	PSO	0	0	0	5.10838e − 79
	BSA	0	0	0	0
	DE	0	2.487e − 5	2.15633e − 3	2.17425e − 5
*F*16	PSO	0	0.15241	0.76207	0.0307907
	BSA	0	0	0	1.22573e − 7
	DE	0	0.03792	0.76218	0.0155155
*F*17	PSO	0.9	0.97700	1	0.00425083
	BSA	0.9	0.9	0.9	7.85006e − 17
	DE	0.9	0.99884	1.054495	0.0027342
*F*18	PSO	−176.1376	−172.8113	−103.6089	1.21073
	BSA	−176.1375	−176.1366	−176.1313	1.1779e − 4
	DE	−176.1376	−140.4818	−49.6449	3.29307

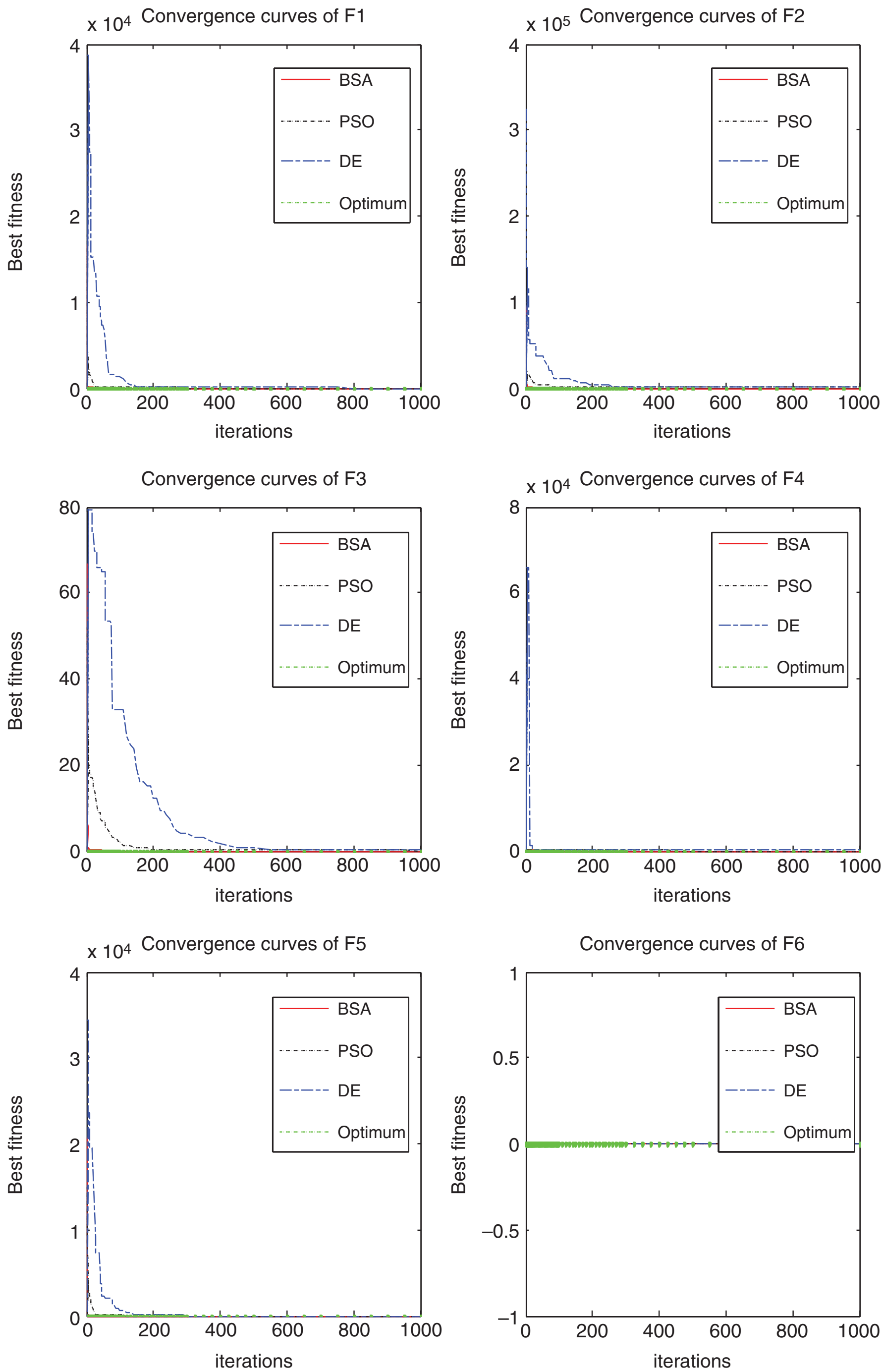

Figure 2. Convergence curves of the three algorithms for solving problems $F1-F18$.

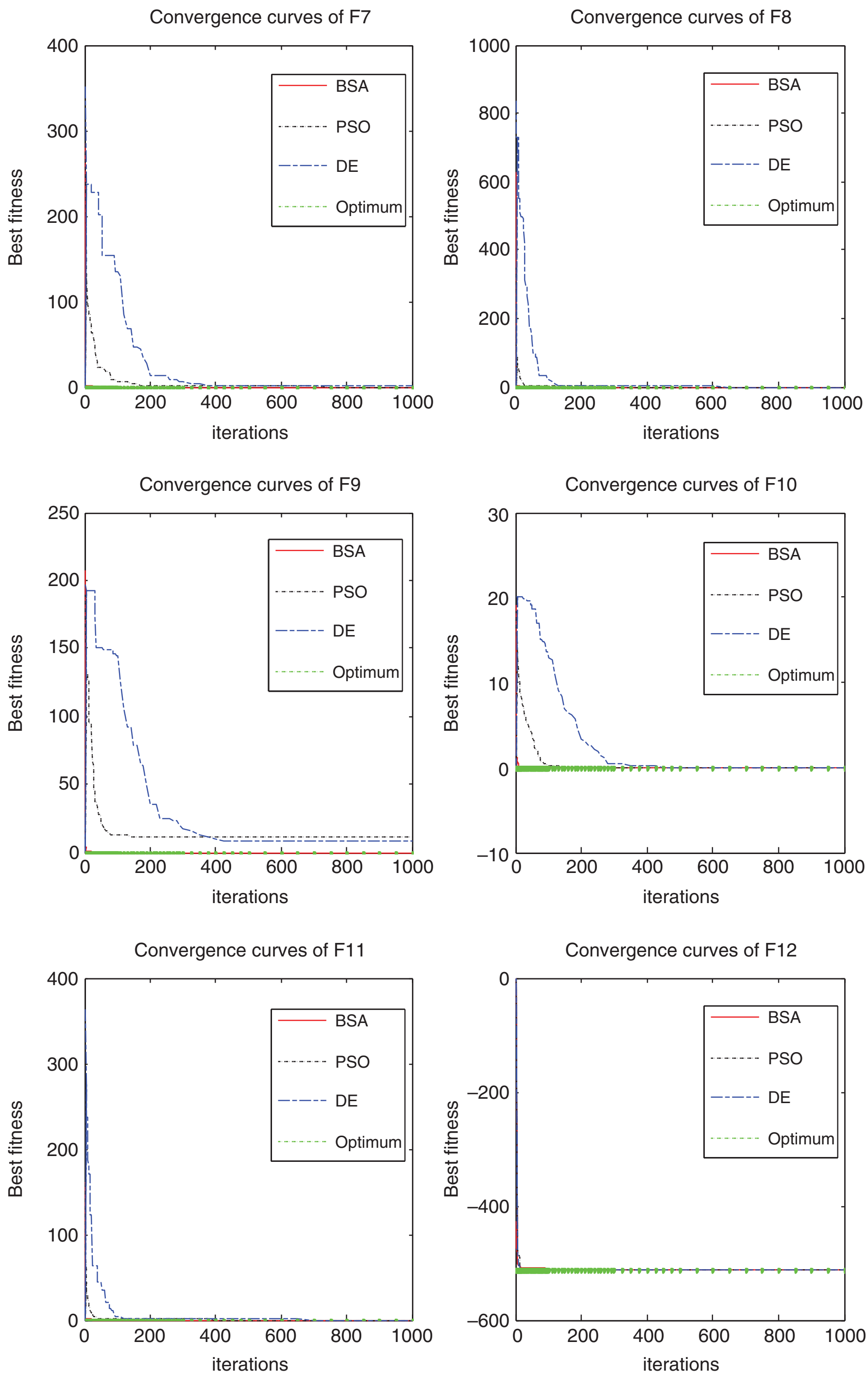

Figure 2. *Continued.*

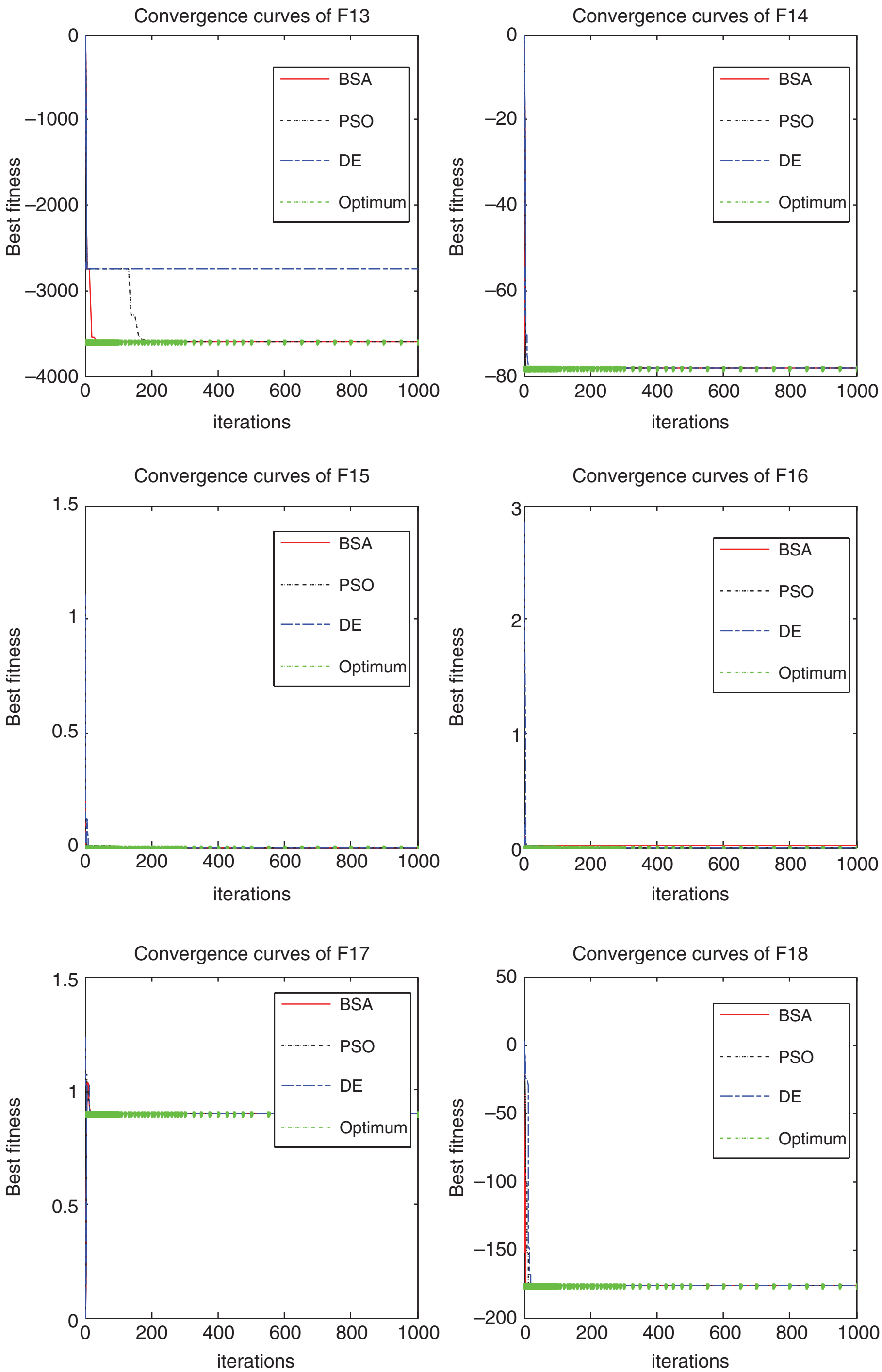

Figure 2. *Continued.*

survival advantage by the social interactions with others. BSA is developed to optimise problems using the swarm intelligence extracted from the bird swarms.

The innovation in this paper lies not only in efficiently extracting the swarm intelligence from the bird swarms to optimise problems, but also in making BSA an innate integration algorithm. PSO and the mutation operator of DE are the special cases of BSA under appropriate simplifications. The four search strategies in BSA make BSA easily extensible. Besides obtaining the merits of PSO and DE, BSA has its own merits. By mimicking birds' vigilance behaviours and the producers' behaviours, BSA can have good diversity, and thus efficiently avoid prematurity. The performance of BSA is compared with that of PSO and DE. Numerous experiments on 18 benchmark problems show that BSA is more accurate, efficient and robust than PSO and DE.

In fact, we just proposed a uniform framework of BSA. Various representations can be used to interpret the aforementioned rules, and develop new variants of BSA.

How to design an efficient algorithm is still required to be studied in the future. The essence of meta-heuristic algorithm is to look for the balance between exploration and exploitation. To summarise, there mainly exist four categories to improve the performance of BSA.

The first category of BSA's variants can achieve improvements by adjusting parameter configurations. For the parameter C, S and FL, the analyses and conclusions of those corresponding parameters in PSO and DE can be used. It must emphasise that BSA is different from PSO and DE. The parameters should be analysed along with the other related parameters. Meanwhile, we may try to let the frequency of birds' flight behaviours (FQ) change dynamically.

The second category may be realised by introducing auxiliary search strategies to enhance BSA's performance. For example, the LévyFlights may be incorporated into the proposed algorithm when birds fly to other sites.

Defining neighbourhood topologies and introducing multi-swarm techniques into the algorithm are another two feasible ways to enhance the performance of BSA. Besides improving the algorithm mechanism itself, hybridising other metaheuristic algorithms and other optimisation methods into BSA is also a good way to improve the proposed algorithms.

Moreover, future work can also focus on solving discrete, combinatorial and more complex optimisation applications using BSA and its variants.

Disclosure statement

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