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Flower pollination algorithm: a comprehensive review

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Abstract Flower pollination algorithm (FPA) is a computational intelligence metaheuristic that takes its metaphor from flowers proliferation role in plants. This paper provides a comprehensive review of all issues related to FPA: biological inspiration, fundamentals, previous studies and comparisons, implementation, variants, hybrids, and applications. Besides, it makes a comparison between FPA and six different metaheuristics such as genetic algorithm, cuckoo search, grasshopper optimization algorithm, and others on solving a constrained engineering optimization problem. The experimental results are statistically analyzed with non-parametric Friedman test which indicates that FPA is superior more than other competitors in solving the given problem.

Keywords Flower pollination algorithm · Metaheuristic · Cuckoo search · Genetic algorithm · Optimization

1 Introduction

"Imagine the organisms of today's world as being the results of many iterations in a grand optimization algorithm. The cost function measures survivability, which we wish to maximize" (Haupt and Haupt 2004). Thus, we can say that optimization algorithm is a simulation of nature evolution phenomena of organisms to reach their present optimized state. From time to time, many ecological inspirations are appointed for developing artificial intelligence metaheuristic algorithms to tackle the stochasticity of optimization problems especially NP-hard ones in various fields such as cloud computing (Yusoh and Tang 2012; Kessaci 2013; Gao et al. 2013; Nesmachnow et al. 2015), Engineering (Yang et al. 2012; Gandomi et al. 2013; Kaveh 2017), Medicine (Chen et al. 2014; Alshamlan et al. 2015; Huson 2017), Geo-

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graphic information system (Saleh 2002, 2003; Wie and Chai 2004; de Lima Júnior 2008), etc.

Although the diversity of metaheuristics inspirations, they follow up a general algorithmic framework that trade-off between exploration and exploitation. Exploration (diversification) makes sure that the algorithm can explore the search space efficiently, often by randomization while Exploitation (Intensification) tends to search around the current best solution. Metaheuristic can guarantee to find a high-quality solution if it can provide a balance between the exploitation and exploration of search space (Blum and Roli 2003; Črepinšek et al. 2013). e.g. at the cellular level, Sampson (1976) introduced genetic algorithm (GA) that mimics the biological evolution process of chromosomes through selection, crossover, and mutation operations. i.e. each candidate solution in the search space is represented as a chromosome that evaluated according to their fitness value. For generating new solutions, parents are selected for breeding which is used to exploit the high fitness solutions in the current generation. Then, some parts of the two selected chromosomes are swapped in crossover phase and mutation is done through randomly change some parts of chromosomes in order to escape from local optima and exploring the search space. Eberhart and Kennedy (1995) combined the evolution computing capabilities with swarm intelligence of animals such as bird flocking or fish schooling to present particle swarm optimization (PSO). During PSO search procedure, each candidate solution (particle) updates its position according to its best position and the swarm's best position they have so far. The exploration and exploitation in PSO are mainly controlled by the inertia weight parameter which determines the influence of the previous velocity on the current velocity of a particle. i.e. in the earlier iterations, the value of inertia weight is large to increase velocity for more exploration. After that, the value of inertia weight is decreased to slow velocity towards zero which indicates more exploitation. Yang and Deb (2009) introduced cuckoo Search (CS) that mimics the aggressive brood parasitism of cuckoo birds. In CS, exploration is performed by cuckoos when they search for nests to replace eggs with their new ones (solutions). If the dropped egg is detected by the host bird, it will be replaced by a new one and exploitation is performed. Also, other algorithms that based on natural behaviors of various animals were introduced such as Bee colony optimization (BCO) (Teodorović and Dell'Orco 2005), Monkey search (MS) (Mucherino and Seref 2007), firefly algorithm (FA) (Yang 2008), Krill Herd (KH) algorithm (Gandomi and Alavi 2012), etc.

As over 80% of all plants on Earth are flowering plants, it was necessary to pay attention of authors to simulate the evolution of flowers. Originally, Kazemian et al. (2006) introduced a new data clustering algorithm that simulating flowers pollination by bees (called FPAB). After that, Yang (2012) proposed flower pollination algorithm (FPA) which mimics a wider conception of flowers reproduction process. Recently, FPA gains a great awareness due to the effective applicability to real life problems.

This paper aims to introduce a comprehensive survey about FPA that including a bird's eye view on all publications related to FPA.

The structure of the rest of the paper is as follows: different applications of FPA are presented in Sect. 2. In Sect. 3, the biological inspiration of the algorithm is discussed and The fundamentals of FPA is reviewed in Sect. 4. The main previous analytical studies and available implementations are presented in Sect. 5. the main FPA variants and hybrids are discussed in Sect. 6 and 7 respectively. A constrained engineering optimization problem is solved in Sect. 8. Finally, conclusion and future works in Sect. 9.

2 Applications

Due to the FPA efficiency and flexibility, it was applied for solving many optimization problems in various real life fields. In this section, a list of the relevant applications will be exhibited in Table 1.

3 Biological inspirations

The angiosperms (the flowering plants) (Takhtajan 2009) are by far the largest phylum of plants that were able to survive since the late Cretaceous Period, about more than 140 million years ago (Eriksson et al. 2000). The reason of this dominance is the optimized pollination process, which is subject to the Darwinian principle "Survival of the fittest" (Frohlich 2003). The flower is a structure specialized to held reproduction organs that responsible for the reproductively of plants via producing the reproductive cells of the plant (pollen and ovule) and then producing seeds which contain dormant offspring plants. Some flowers are unisexual (Imperfect) flowers that contain stamens (male) and carpels (female) reproductive organs in separate flowers while bisexual(Perfect) flowers contain both organs in the same flower.

Pollination (Frankel and Galun 2012) is the process where the male gamete (pollen) is transferred to the stigma so it can fertilize the female gamete. Flowers can have colorful petals, fragrance, and nectar that make a plant more conspicuous to pollinators such as animals, insects, or birds. Some flowers can influence on pollinators to exclusively visit it through the strength of attraction and preserve the flower constancy. Also, by visiting the same flower species, pollinators can ensure nectar supply with less exploring. In some cases, pollen is transferred simply by the wind, diffusion in water, or gravity. Thus, pollination can be classified into two main pollination types: cross-pollination process, and self-pollination process. In the former, pollen is transferred from one flower to another flower in a different plant. In the latter, pollen is transferred from one flower to different flower of the same plant. Also, pollination can have another classification based on pollinators (either they are living or nonliving) into Biotic-pollination and Abiotic-pollination. Biotic-pollination occurs when an animal or insect visits a flower for eating pollen or sipping nectar, some pollen grains attached to its body. If the animal visits another flower for the same reason, pollen can transfer to the stigma of flower and may result in fertilization of the flower. Abiotic-pollination has a limited occurrence as pollen is transferred by the wind, diffusion in water or gravity when the anthers are approximate to the stigma so that it is lacking in precision (see Fig. 1).

4 Flower pollination algorithm

The main idea of FPA arises from the nature pollination principles discussed before. i.e. Keeping alive more fittest flowers in species through the reproduction process. In FPA, a flower and/or a pollen is equivalent to a candidate solution (it was assumed that there is only one flower in each plant and each flower only produce one pollen). During the optimization process, diffusion through search space is done by biotic and cross-pollination where the pollen movement is represented by Lévy flight. Briefly, Lévy flight is a random walk based on a random step that drawn from Lévy distribution. As a side note, " Lévy flight or walk? " the more precious is Lévy flight as the time between both large and small random steps are constant (Bazant 2005). However, they were used interchangeably in the literature (Jamil and

Table 1 FPA applications

Field	Applications
Computer science	Cloud computing (Pathak and Mahajan 2015) Data clustering (Jensi and Jiji 2015; Agarwal and Mehta 2016; Wang et al. 2016) Optical wavelength division multiplexing (WDM) systems channel allocation (Jain et al. 2015) Wireless sensor networks (WSNs) optimization (Sharawi et al. 2014; Harikrishnan et al. 2015; Goyal and Patterh 2015; Binh et al. 2016) Graph coloring problem (Bensouyad and Saidouni 2015) Adaptive equalizer (AE) optimization (Banerjee and Chattopadhyay 2016)
Bioinformatics	Neural networks training (Chakraborty et al. 2015; Chiroma et al. 2016) Feature selection (Zawbaa et al. 2015; Yamany et al. 2015; Nasser et al. 2015; Xu et al. 2017b)
Operation research	Integer programming problem (El-henawy and Ismail 2014; Khalil 2015) Economic load dispatch problem (Prathiba et al. 2014; Azis et al. 2015; Abdelaziz et al. 2016; Gonidakis 2016; Velamuri et al. 2016; Vijayaraj and Santhi 2016; Putra and Saputra 2016; Shilaja and Ravi 2017) Fractional programming problems (Metwalli and Hezam 2015) Distributed generation (DG) optimal locations (Oda et al. 2015; Reddy et al. 2016) Optimal line flow (OLF) (Shilaja and Ravi 2016) Ratios optimization problems (ROPs) (Abdel-Baset and Hezam 2015) Resource constrained project scheduling problem (RCPSP) (Bibiks et al. 2015) Assembly sequence optimization (Mishra and Deb 2016) Vehicle path planning problem (Gautam et al. 2015; Zhou and Wang 2016) Congestion management (CM) problem (Deb and Goswami 2016; Verma and Mukherjee 2016)
Imaging science	Fractal image compression (Kaur et al. 2013) Medical image segmentation (Wang et al. 2015) Visual tracking system (Gao et al. 2016) Atomic potential matching (APM) (Zhou et al. 2016a)
Food industry	Liquid–liquid equilibrium modeling (Merzougui et al. 2016) Shrinkage of triaxial porcelain containing palm oil fuel ash (Zainudin et al. 2017) Generating healthy nutritional meals for older adults (Pop et al. 2017)
Meteorology	Wind speed forecasting (Heng et al. 2016)
Medicine (ophthalmology)	Retinal vessel segmentation (Emary et al. 2014; Emary et al. 2017) Electroencephalogram (EEG) person identification (Rodrigues et al. 2016) Fetal head segmentation (Kusuma et al. 2016)

Table 1 continued

Field	Applications
Education	Selection of university academic credits (Ochoa et al. 2014)
Engineering	Truss structures Sizing optimization (Bekdaş et al. 2015a, b, c, 2017a, b) Solar photovoltaic (PV) systems parameter estimation (Alam et al. 2015; Benkercha et al. 2016; Ram et al. 2017; Ram and Rajasekar 2017a, b; Xu and Wang 2017) Multi-pass turning parameters (Xu et al. 2017a) Control of a multi-area power system (Dash et al. 2016) Groutability estimation of grouting processes with cement grouts (Hoang et al. 2016) Optimal power flow (OPF) problem (Regalado et al. 2015; Mahdad and Srairi 2016; Chattopadhyay and Banerjee 2016) Optimal reactive power dispatch (ORPD) problem (Lenin et al. 2014; Sakthivel et al. 2016) Load frequency control (Lakshmi et al. 2016; Jagatheesan et al. 2017; Pravallika and Rao 2016) Antenna positioning problem (Saxena and Kothari 2016; Singh and Salgotra 2018; Dahi et al. 2016; Bairwa et al. 2016) Optimal capacitor locations (Abdelaziz et al. 2016a, b; Tamilselvan and Jayabarathi 2016; Sudabattula and Kowsalya 2016; Namachivayam et al. 2016) Dynamic multi objective optimal dispatch (DMOOD) For wind-thermal system (Dubey et al. 2015) Inverse kinematic problem (PUMA Robot), hydrocarbon combustion problem, and the double azeotrope calculation problem (Platt 2014) Pin-jointed plane frames optimization (Nigdeli et al. 2015; Nigdeli et al. 2016) A three-bar truss systems optimization (Nigdeli et al. 2016) Deflection minimization of I-beams (Nigdeli et al. 2016) Vertical tubular columns optimization (Nigdeli et al. 2016) Weight optimization of cantilever beams (Nigdeli et al. 2016) The identification of infinite impulse response (IIR) models (Cuevas et al. 2017) Mass dampers tuning (Bekdaş et al. 2017b, Nigdeli et al. 2017a, b) PV/wind/battery stand-alone system optimization (Tahani et al. 2015) Static VAR compensator damping controller design (Abdelaziz and Ali 2015; Kumar et al. 2015) Placement of distribution transformers in a low-voltage grid (Huang et al. 2015) Hydrothermal scheduling (HTS) problem (Dubey et al. 2014) Multi-machine system optimal control (Pambudy et al. 2014) Optimal relay coordination (Trivedi et al. 2015) Manufacturing cell design (Soto et al. 2016) Design of wideband digital integrators and differentiators (Mahata et al. 2017)

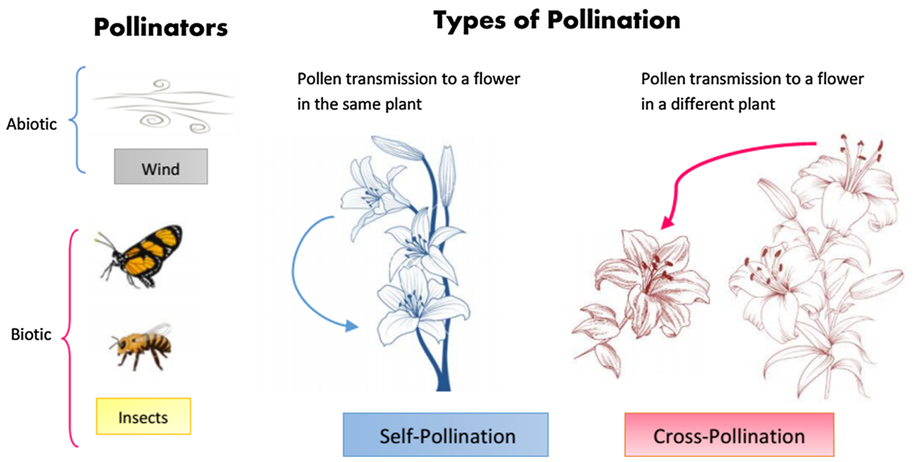

Fig. 1 The pollinators and pollination types

Initialize parameters with switching probability $p \in [0,1]$;
Generate initial population of flowers randomly;
Evaluate initial population and find the current best solution $gbest$;
while (stopping criterion not satisfied) **do**
  For each flower
    if $rand() < p$
      Global pollination : $x_i^{t+1} = x_i^t + L(x_i^t - gbest)$; // Based on Lévy step
    else
      Select two random solutions x_j^t and x_k^t ;
      Local pollination : $x_i^{t+1} = x_i^t + \epsilon(x_j^t - x_k^t)$;
    end if
    Evaluate new solutions;
    Update solutions with better new ones;
  end for
  Keep the current best solution;
end while

Fig. 2 FPA Pseudocode

Zepernick 2013). Lévy distribution is a probability distribution with heavy power-law tails (Shlesinger et al. 1995) that used to describe anomalous diffusion which has infinite mean and infinite variance that cause much longer movement from its current position. Thus, it is more efficient in the search space exploration (Fredriksson 2010).

Abiotic self-pollination represents the intensification step.FPA efficiently mix exploitation and exploration to ensure the quality of the search, a random switching between them is done (See Fig. 2). FPA depends on some idealized principles as following (Yang 2012):

R1: Biotic, cross-pollination acting as global search via Lévy flight.
R2: the local search is performed by abiotic and self-pollination process.
R3: Flower constancy can be involved due to the similarity of two flowers.
R4: The switching between local and global search is performed by a random probability $\in [0, 1]$.

The algorithm starts with generating initial population randomly which evaluated in order to determine the current best solution. For calculating a new solution, the pollination type should be determined at first according to a predetermined probability p (*R4*). i.e. a random number $r \in [0, 1]$ is generated and if r is less than p then the global pollination and the flower constancy (*R1 and R3*) can take place as following:

$$x_i^{t+1} = x_i^t + \gamma L \left(x_i^t - gbest \right) \tag{1}$$

where x_i^t is a solution i at time t, $gbest$ is the current best solution, γ is a scaling factor, and L is a step size drawn from Lévy flight as:

$$L\left(s, a\right) \sim \frac{\lambda \Gamma\left(\lambda\right) \sin\left(\frac{\pi\lambda}{2}\right)}{\pi} \frac{a}{s^{1+\lambda}}, \ |s| \rightarrow \infty \tag{2}$$

where $\Gamma\left(\lambda\right)$ is the standard gamma function with an index λ,a is a control parameter for the tail amplitude of the distribution (Bazant 2005) ($a = 1$ in the proposed FPA),and a large steps ($s \gg s_0 > 0$) which is generated according to the following nonlinear transformation (Mantegna algorithm (Mantegna 1994)) as:

$$s = \frac{U}{|V|^{\lambda^{-1}}} \tag{3}$$

where U and V are two random samples drawn from a Gaussian normal distribution with mean equals zero, and standard deviations σ_u and σ_v:

$$U \sim \left(0, \sigma_u^2\right), V \sim \left(0, \sigma_v^2\right) \tag{4}$$

$$\sigma_u = \left[\frac{\Gamma\left(1+\lambda\right)}{\lambda \Gamma\left(\left(1+\lambda\right)/2\right)} \cdot \frac{\sin\left(\frac{\pi\lambda}{2}\right)}{2^{(\lambda-1)/2}} \right]^{1/\lambda}, \ \sigma_v = 1 \tag{5}$$

Note that, the standard deviation σ_v is set to 1 as σ_u and σ_v can't be chosen independently for any value of.

Otherwise, if r is greater than p then the local pollination and the flower constancy (R2 and R3) are performed as:

$$x_i^{t+1} = x_i^t + \varepsilon \left(x_j^t - x_k^t \right) \tag{6}$$

where x_j^t and x_k^t are two randomly selected solutions and $\varepsilon \in [0, 1]$ is a random number. After that, the current best is updated and the search iterations resume until the termination criteria.

4.1 User defined parameters

Roughly speaking, the user-defined parameters of FPA are: population size, switch probability p, Lévy distribution index λ, and scale factor γ. In order to determine the best definition of their values, different studies were proposed. e.g. Łukasik and Kowalski (2015) showed that the size of the population of solutions is determined according to the problem under consideration but it is recommended to limit population size if satisfactory outcomes are achieved as the complexity of FPA is $O\left(n\right)$. Regarding, the switch probability which determines the percentage of diversification and intensification during research, Yang et al. (2014) assumed that $p = 0.8$ is suitable for most applications. On the other hand, Draa (2015) supposed that the best value of probability is $p = 0.2$. For Lévy distribution, Mantegna (Bazant 2005) proved that the best value of λ index is between [0.75, 1.95] and the scale factor for controlling step size can take any positive value. Yang et al. (2014) used the scale factor $\gamma = 0.01$ for FPA as it can prevent pollen from flying away.

5 Performance analysis and implementation

Since the invention of FPA in 2012, different studies were proposed to evaluate the performance of FPA. Next, FPA main studies will be briefly discussed.

5.1 Analytical studies

Łukasik and Kowalski (2015) studied the FPA properties in continuous optimization with a detailed parameter setting analysis especially switching probability. Beside the previous point of view, the authors showed that it is better to use high values switching probability. Moreover, FPA was compared with PSO and the experimental results showed that both algorithms have similar performance for selected test benchmark functions from CEC 2013 competition (Liang et al. 2013).

Draa (2015) critically examined the main FPA previous related papers and focused on the discussion of imperfections. Also, the author analyzed the effect of switching probability value on the FPA performance. The author compared FPA with many improved metaheuristics, although it is a basic version and need refinements. i.e. two comparisons were performed on CEC 2013 and CEC 2011 (Das and Suganthan 2010) benchmarks. Firstly, FPA was compared with Sinusoidal Differential Evolution Algorithm (SinDE) (Draa et al. 2015),Super-fit multicriteria adaptive differential evolution (SMADE) (Caraffini et al. 2013), differential evolution with concurrent fitness based local search(DEcfbLS) (Poikolainen and Neri 2013), adaptive differential evolution (DE) with twelve competing strategies (b6e6rl) (Tvrdík and Poláková 2013), Teaching and learning best differential evoltuion with self adaptation (TLB-Sade) (Biswas et al. 2013), and Covariance Adaptation Matrix Evolution Strategy with Re-sampled inheritance search (CMA-ES-RIS) (Caraffini et al. 2013), respectively. According to Wilcoxon rank-sum statistical comparison, the first comparison indicated that the overall performance of FPA is worst than the competitors. Secondly, FPA was compared with adaptive differential evolution with optional external archive (JADE) (Zhang and Sanderson 2009), DE with selective pressure mutation (RBDE) (Sutton et al. 2007), self-adaptive DE (SaDE) (Qin et al. 2009), Success-History DE (SHADE) (Tanabe and Fukunaga 2013),and variants of successful-parent-selecting DE algorithm (SPS-DE) (SPS-JADE, SPS-RBDE, SPS-SaDE, and SPS-SHADE) (Guo et al. 2015). The experimental results were analyzed by a Holm Bonferroni-based statistical analysis (Holm 1979) which denoted that FPA still need enhancements to confront the competitors. The rest of the paper studied and compared some variants of FPA.

Yang et al. (2017) introduced a mathematical analysis of FPA using Markov chain theory (Jiang et al. 2007; Wang et al. 2012) and proved that FPA can converge to optimal solution. In addition, an experiment was made on well-known benchmarks in order to exhibit the convergence ability of FPA in practical.

5.2 Comparative studies

Many studies were proposed to evaluate the performance of FPA by the comparisons with other metaheuristics on solving various optimization problems as examples:

Sakib et al. (2014) compared FPA with Bat Algorithm (BA) (Yang 2010) on different unimodal and multimodal benchmarks and the experimental results show that FPA outperforms BA in terms of convergence, solution quality, and consistency on continuous optimization problems. Pandya et al. (2015) compared both algorithms with PSO, but on Optimal Power Flow (OPF) problem of highly stressed modified IEEE 300-bus test system. The results show that BA offers better performance than FPA and PSO on the given problem. Also, Hegazy et al. (2015) compared between the previous algorithms, modified cuckoo search (MCS) (Walton et al. 2011), and artificial bee colony (ABC) (Karaboga 2005) on least square support vector machine (LS-SVM) optimization. The best results were achieved by FPA-LS-SVM method. Nasser et al. (2016) compared FPA with harmony search (HS) for software testing and the experimental results show that the performance of both metaheuristics is almost the same, although HS outperforms FPA in many cases. Ouadfel and Taleb-Ahmed (2016) studied the performance of FPA on thresholding of multilevel image and mainly compared with Social spiders optimization(SSO) algorithm (Cuevas et al. 2013). The experimental results showed that FPA is more suitable for small numbers of thresholds rather than larger ones. Rathasamuth and Nootyaskool (2016) compared between FPA, PSO, and GA on discrete search space. The results indicated that FPA has better convergence rate than others.

5.3 Implementation

As previously mentioned, the basic implementation of FPA was done using Matlab language by Yang. After that, many contributions were introduced for implementing FPA in different languages to accommodate to various applications. For example, many object-oriented based languages like C++and java languages were used for implementing FPA in Widihananta (2014) and Yang (2016) respectively. Bhatia et al. (2016) introduced FPA toolkit in LabVIEW™. Besides, R language was considered in Putra and Anggorowati (2016) to implement FPA. R language is a well-developed, simple and effective language and environment especially used for statistical computing and graphics (Ripley 2001).

6 Variants of FPA

6.1 Improvements

Although the efficiency of FPA, it has some drawbacks such as time consuming and premature convergence for a number of given problems. So that, Several improvements were proposed to overcome these drawbacks. The adjustment of the algorithm can be made to the global search or local search procedures or both. Next, the major improvements of FPA are briefly exhibited.

6.1.1 Modified FPA (MFPA)

Dubey et al. (2015) controlled the local pollination by a new constant scaling factor instead of a random number to increase convergence. Also, an additional exploitation step was added for adjusting the best solution. MFPA was used to solve economic dispatch problems of electrical power systems. The experimental results showed that the proposed algorithm is superior for solving small and medium scale instances while for large instances the proposed algorithm still required enhancement.

6.1.2 Improved FPA with Chaos (IFPCH)

Chaotic maps (Logistic map, Chebyshev map, Tent map, etc.) are evolution functions that generate a deterministic bounded sequence of random numbers based on the initial condition with different time domain (continuous or discrete). Abdel-Raouf et al. (2014) used the chaotic maps instead of the random numbers because of being random-like, non-period, and non-converging for parameter adaptation. In IFPCH, the switching probability, Lévy step, and local pollination random number are defined according to the selected chaotic map. The proposed algorithm was applied to calculate the numerical value of definite integrals. The results showed that adding chaotic maps to FPA effect significantly on its performance.

6.1.3 FPA with dimension by dimension improvement (DDIFPA)

Wang and Zhou (2014) improved FPA through employing three strategies: local neighborhood search strategy (LNSS): enhances local pollination where only the best neighbor solutions with a predefined topology are used to update solution instead of the whole population. Dimension by dimension evaluation and improvement strategy (DDEIS): deals with multi-dimensional problems by updating dimension by dimension. Dynamic switching probability strategy (DSPS): responsible for modifying the switching probability with respect to the current iteration and the total number of iterations. DDIFPA was tested on 12 benchmarks. The results indicated that DDIFPA can exploit the search space more efficient for the unimodal and get more accurate solutions for multimodal benchmarks than FPA.

6.1.4 FPA with complex-valued encoding (CFPA)

The complex-valued encoding scheme was inspired from amphiploid where each chromosome consists of two alleles (the real gene and the imaginary gene). In CFPA (Zhao and Zhou 2016), each candidate solution consists of two vectors: the real parts and the imaginary parts which updated in parallel to increase the population randomness and the performance of FPA. The comparison between FPA and CFPA on 10 well-known benchmarks with high dimension showed that CFPA is faster and more robustness than FPA.

6.1.5 Elite opposition-based FPA (EOFPA)

Zhou et al. (2016b) considered three subsidiary enhancements: global elite opposition-based learning strategy (GEOLS) which applied for getting better solutions by expanding the exploration phase via evaluating the candidate solutions and their opposite solutions simultaneously. In local self-adaptive greedy strategy (LSGS), a greedy solution is calculated and highly tuned in early iterations to escape from local optima afterward the adjustment of the greedy solution become smaller at the end of iterations. Dynamic switching probability strategy (DSPS) was applied to dynamically adjust the switching probability value according to the iterations. EOFPA was tested on 18 benchmark functions and two engineering constrained problems. The results exposed that the proposed algorithm is more accurate and stable than FPA.

6.2 FPA adaptation to search space

Due to the efficiency of the basic FPA for handling single objective optimization problems in continuous search spaces, various studies were submitted to extend the application FPA to other search environments.

6.2.1 *Combinatorial space*

Rodrigues et al. (2015) proposed a binary version of FPA for handling the discrete binary problems where the search space is a d-dimensional boolean lattice. In order to draw the continuous search space into a binary one, sigmoid function (SF) is used as:

$$x_{ij} = f(x) = \begin{cases} 1, & rand() \leq \frac{1}{1+\exp(-x_{ij})} \\ 0, & otherwise \end{cases} \tag{7}$$

Bensouyad and Saidouni (2015) used a simple round function for getting a solution vector of integer numbers. Mishra and Deb (2016) considered another discretization method by defining solutions as strings of two-digit numbers, then applying the FPA calculations.

6.2.2 *Multi-objective optimization*

Yang et al. (2013, 2014) introduced multi-objective FPA to deal with multiple conflicting objectives of a wide range of optimization problems. The authors accommodated a simple weighted sum approach to transform the multiple objectives problem to single objective one. In other words, these weights values determine the priority of each objective. For each set of weights, a Pareto front is generated. The generated solution become the Pareto optimal if the corresponding sum of weights values is positive and larger enough.

7 Hybridization of FPA

The prosperity of FPA most appears in the case of hybridization with other optimization techniques (e.g. metaheuristics, machine learning, exact methods, etc.). Hybridization can be done in low or high level according to the interference level between hybridized methods. i.e. high-level hybridization indicates that low interference between the internal work of hybridized algorithms while low-level hybridization means that only an extracted step of metaheuristic is exported to another metaheuristic. Moreover, the execution of the hybridized algorithms can be done in different order (sequential, interleaved, or parallel). In other words, the hybridized algorithms may collaboratively exchange information or integrated with a master one that operates the search procedure during the search process. For more information, see Raidl (2006), Blum and Roli (2008) and Blum et al. (2010).

Nabil (2016) combined local pollination with the clonal selection methodology (De Castro and Von Zuben 2000) which mimics the theoretical immunology principles. Thus, if the switching condition directs the algorithm to local search, a population of the best antibodies (solutions) is selected from the current population. Then, the higher affinities antibodies are cloned in order to generate more antibodies against the antigen (objective function). Those antibodies are not cloned are replaced by new ones via local pollination. The hybridized algorithm is able to find more accurate solutions than FPA as it comprises the Lévy flight based exploration capabilities of FPA and the good exploitation capabilities of the clonal selection algorithm. Also, a binary version of the proposed algorithm was presented in Sayed et al. (2016).

Kalra and Arora (2016) hybridized FPA with firefly algorithm (FA) (Yang 2008). First, the local search is done by FA and the current best is determined. Then, FPA switching condition directs the search process either to FA global search or FPA local search. The proposed algorithm guarantees faster convergence and lower computational time. Also, Yang et al.

(2013) powered eagle strategy (ES) (Yang and Suash 2010) with FPA local search step for enhancing exploitation and exploration. While Chakraborty et al. (2015) combined FPA global search with gravitational search algorithm (GSA) (Rashedi et al. 2009) local search via dynamic switch probability and weights mechanisms. The proposed algorithm reached more classification accuracy.

Chakraborty et al. (2014) combined FPA with differential evolution (DE) and replaced the switching probability with a new dynamic adaptive weight. First, DE is applied then the population is updated by the new FPA unified pollination equation which based on dynamic weight. While Tsai et al. (2017) merged FPA with DE in a parallel schema. i.e. both algorithms are applied at the same time in reciprocity manner. During the search processing, the best solutions are stored and interchanged between both algorithms via communication strategy. Another parallel execution for FPA was introduced by Salgotra and Singh (2016),but with BA.

In Ramadas and Kumar (2016), Abdel-Baset and Hezam (2015) and Abdel-Baset and Hezam (2016), DE, GA, and simulated annealing (SA) (Tahani et al. 2015; Kirkpatrick et al. 1983) respectively were employed sequentially to adjust the solution obtained by FPA. Whereas, Abdel-Raouf et al. (2014) used FPA for improving the solution obtained by chaotic harmony search. While in Abdel-Raouf and Abdel-Baset (2014) FPA improved the PSO final solution. Ku-Mahamud (2015) proposed two combinations between FPA and Ant colony system (ACS) (Dorigo and Gambardella 1997). The first combination only considered the FPA global pollination for enhancing the exploration capabilities of ACS while the second combination used FPA for adjusting the final result of ACS. Also, Abdel-Baset and Hezam (2016) combined FPA and SA, but in a different manner. Thus, the initial solution is generated by SA. Then, a new solution is generated by FPA, and the acceptance of these new solutions is carried out by SA.

In Hezam et al. (2016), Tabu search (TS) (Glover and McMillan 1986) and FPA were interactively combined. i.e. the solutions obtained by FPA are preserved by TS. Nigdeli et al. (2017) introduced a priority switching strategy in order to switch between FPA and harmony search (HS). First, the initial population is generated randomly. After that, the exchange between FPA and HS is randomly determined and priority index is decreased with respect to the iteration number. If the resultant solution (from FPA or HS) is better than the existing ones, priority index is increased to have more chance.

Ram et al. (2017) connected FPA with artificial bee colony (ABC) and simplex method. First, FPA is applied, but the global search is replaced by Elite based mutation process. After that, the resultant solution is evaluated and the current best is updated. If the resultant solution fails to replace the current best solution, a counter is incremented. When the counter reaches the limit, the solution is enhanced with the simplex method. The same approach was followed in Xu et al. (2017b). The authors applied simplex method after FPA if the counter reaches the limit. Besides in Xu and Wang (2017), an additional condition stage was added for switching between calculating the opposite population of the current one or not.

Furthermore, FPA can be combined with other methods in order to performance enhancement. Valenzuela et al. (2017) combined FPA with fuzzy inference system for a dynamical change of the switching probability.

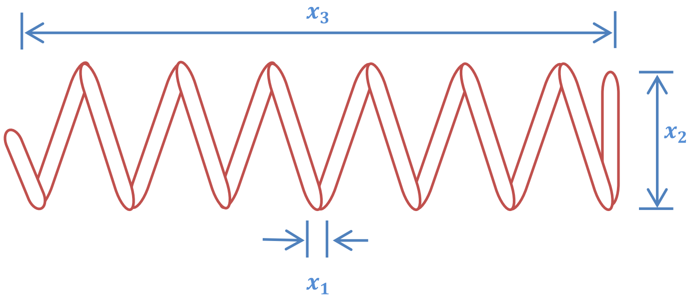

Fig. 3 Spring design problem

8 Tension/compression spring design optimization problem

8.1 Problem description

The main objective of spring design optimization problem (Arora 1989; Belegundu and Arora 1985) is to minimize the volume $f(X)$ of a coil spring under a tension/compression subject to constraints of minimum deflection ($g_1(X)$), shear stress ($g_2(X)$), surge frequency ($g_3(X)$), limits on outside diameter ($g_4(X)$), and on design variables (See Fig. 3). The mathematical formulation can be expressed as:

$$
\begin{aligned}
&\min \quad f(X) = (x_3 + 2)\, x_2 x_1^2 \\
&s.t. \\
&g_1(X) = 1 - \frac{x_2^3 x_3}{71785 x_1^4} \leq 0 \\
&g_2(X) = \frac{x_2(4x_2 - x_1)}{x_1^3(12566 x_2 - x_1)} + \frac{1}{5108 x_1^2} - 1 \leq 0 \\
&g_3(X) = 1 - \frac{140.45 x_1}{x_2^2 x_3} \leq 0 \\
&g_4(X) = \frac{2(x_1 + x_2)}{3} - 1 \leq 0 \\
&0.05 \leq x_1 \leq 2,\ 0.25 \leq x_2 \leq 1.3,\ 2 \leq x_3 \leq 15
\end{aligned}
$$

where x_1 is the wire diameter, x_2 is the mean coil diameter, and x_3 is the length or number of coils.

8.2 Experimental results

In order to test the performance of FPA in solving engineering optimization problems, it is applied to solve the previous problem. In addition, the performance of FPA is compared with the following metaheuristic: genetic algorithm (GA) (Sampson 1976), particle swarm optimization (PSO) (Eberhart and Kennedy 1995), ant colony optimization (ACO) (Dorigo 1992), cuckoo search (CS) (Yang and Deb 2009), grey wolf optimizer (GWO) (Mirjalili et al. 2014), and grasshopper optimization algorithm (GOA) (Saremi et al. 2017). For parameter settings, the number of search agents is set to 100 agents and the maximum number of

Table 2 Parameters settings of FPA and other metaheuristics

Metaheuristics	Parameters
GA	Crossover percentage = 0.7 Mutation percentage = 0.3 Mutation rate = 0.1
PSO	learning parameters = 2
ACO	Intensification factor = 0.5 Deviation-distance ratio = 1
CS	Switching probability = 0.25 Lévy stepsize scaling factor = 0.01 Lévy distribution index λ = 1.5
GWO	(All parameters are updating during run)
GOA	The reduction coefficient minimum value = 0.00004 The reduction coefficient maximum value = 1
FPA	Switching probability = 0.8 Lévy stepsize scaling factor = 0.01 Lévy Distribution index λ = 1.5

iterations is set to 3000 iterations (the other parameters of each algorithm are given in Table 2). Table 3 shows the statistical results of 30 independent trials. As shown, FPA is able to find the smallest volume. Also, FPA is characterized by stability and this is evident by mean and standard deviation values. Figure 4 exposes the convergence of FPA and other competitors in the first 30 iterations. It is clear that FPA converges faster than other metaheuristics.

Besides, the experimental results are analyzed with nonparametric Friedman test (Gibbons and Chakraborti 2011) to show the differences in performance between FPA and the compared algorithms. The experimental results are analyzed with nonparametric Friedman test to show the differences in performance between the proposed algorithm and the compared algorithms. Friedman Test is a non parametric, rank-based version of one-way ANOVA with repeated measures which can be performed on more than two dependent samples. In other words, Friedman test compares the means of three or more variables measured on the same respondents. The null hypothesis (H0) of Friedman test is there are no systematic differences among the treatments being compared, while the alternative hypothesis (H1) is contrary to H0. As shown in Fig. 5, the results of Friedman test indicate the rejection of H0 and the acceptance of H1. i.e. the p value is less than the level of significant ($\alpha = 0.05$) which indicates that the compared algorithms are different in performance. Figure 6 shows Friedman ranked mean of each metaheuristic. As shown, the performance of FPA is better than the competitors as it has the lower ranked mean. All experiments are carried out on MATLAB© R2015a and a 64-bit operating system with a 2.60 GHz CPU and 6 GB RAM.

Table 3 Descriptive statistics of FPA and other metaheuristics for tension/compression spring design problem

Algorithm	Mean	SD	Minimum	Maximum	Percentiles			Average time (s)
					25th	50th (median)	75th	
GA	1.3687E − 02	9.6806E − 04	1.2686E − 02	1.7788E − 02	1.2978E − 02	1.3479E − 02	1.4083E − 02	2.2662E + 01
PSO	1.3078E − 02	4.6070E − 04	1.2719E − 02	1.5040E − 02	1.2722E − 02	1.3193E − 02	1.3193E − 02	1.5452E + 00
ACO	1.3933E − 02	4.3307E − 04	1.3223E − 02	1.5017E − 02	1.3635E − 02	1.4041E − 02	1.4183E − 02	1.8980E + 01
CS	1.2783E − 02	1.3542E − 04	1.2666E − 02	1.3266E − 02	1.2688E − 02	1.2735E − 02	1.2831E − 02	2.1342E + 01
GWO	1.2687E − 02	1.8795E − 05	1.2667E − 02	1.2721E − 02	1.2671E − 02	1.2679E − 02	1.2700E − 02	7.7808E + 00
GOA	1.5492E − 02	4.5892E − 03	1.2706E − 02	3.0455E − 02	1.2759E − 02	1.3488E − 02	1.6772E − 02	1.0302E + 03
FPA	1.2665E − 02	1.2640E − 07	1.2665E − 02	1.2666E − 02	1.2665E − 02	1.2665E − 02	1.2665E − 02	1.4691E + 01

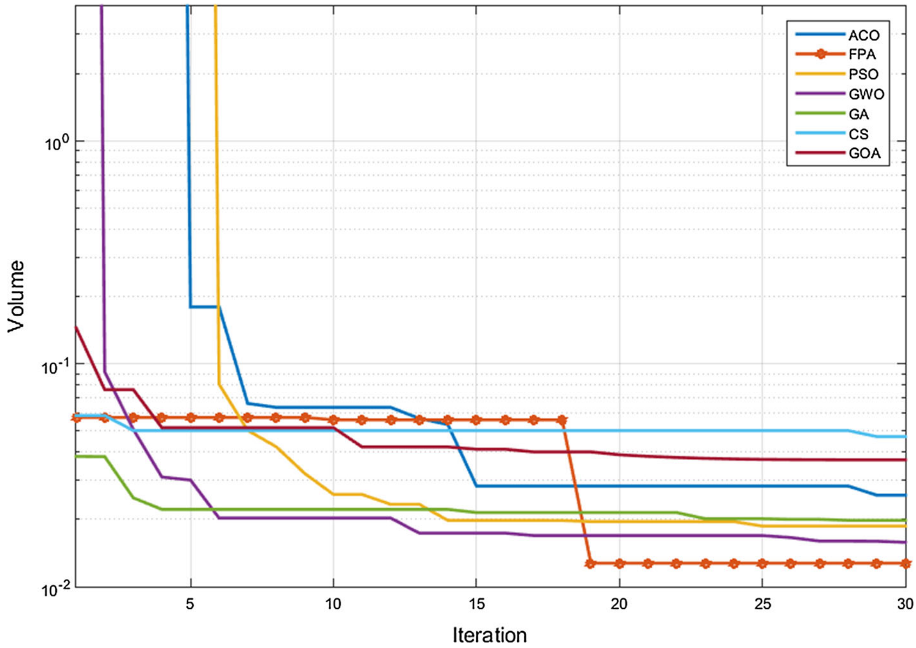

Fig. 4 Convergence of FPA and other metaheuristics

Friedman's ANOVA Table

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	666.983	6	111.164	143.01	2.32025e-28
Error	172.517	174	0.991		
Total	839.5	209			

Fig. 5 Friedman test results

9 Conclusion

However, metaheuristics are not problem specific, choosing the appropriate metaheuristic for the given problem should be considered, i.e., the more adaptation to the given problem, the more efficient metaheuristic. This is, what characterizes FPA since it owns a few parameters that need to be adjusted. As consequence, FPA has recently applied to many application areas. Whereas, it is clear that the basic FPA still need some amendments to improve its performance and disposal from premature convergence and time-consuming.

This paper gives an overview of FPA main structure, previous studies, variants, and applications to provide interested researchers with a comprehensive overview about FPA. Also, an engineering case study "tension/compression spring design problem" is solved with FPA and 6 different metaheuristics and the experimental results are statistically analyzed with Non-Parametric Friedman test. The statistical results indicate that the performance of FPA is superior for a given problem.

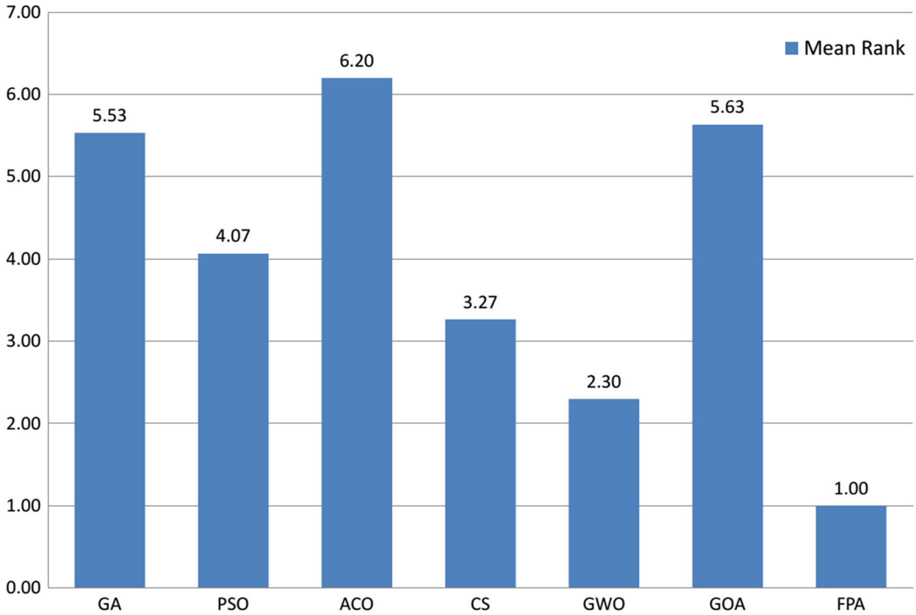

Fig. 6 Friedman ranked mean of FPA and other metaheuristics

For future works, there are many applications areas are rarely invaded which has several problems can be solved potentially by FPA such as Neural Networks, Medicine, and chemistry, etc. Also, the modification of standard FPA still prevailing area needs more research.

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