A Brief Overview of Firefly Algorithm

Bilal and Millie Pant

Abstract Past one decade has seen a tremendous increase in the development of nature-inspired metaheuristics (NIM). In this paper, we provide a brief review on firefly algorithm (FA), one of the recent developments in the field of NIM for solving optimization problems. FA first proposed by Xin-She Yang in 2008 is a swarm intelligence-based algorithm slowly gaining popularity for solving continuous, multi-objective, dynamic and noisy, discrete, nonlinear, and multi-dimensional problem. It has a simple structure and is easy to apply on a wide range of problems as shown by different researchers.

Keywords Firefly algorithm · Nature-inspired metaheuristics (NIM) Swarm intelligence

1 Introduction

Situations arising in almost all spheres of human activities can be designed mathematically as optimization problems. Mathematically, the optimization problems can be categorized in several ways; for example, as continuous problems (dealing with real functions [1, 2]), constrained problems (having limitations or bounds [3, 4]), combinational problems where solution is determined from finite or infinite sets [5, 6–8] multimodal problems having large number of local solutions better than all neighboring solutions, but not good as the globally optimal solution [9], multi-objective problems, where the fineness of a solution is defined by its performance relative to different objectives [10, 11], and non-stationary problems which are dynamic and noisy [12].

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Often these problems are challenging and require a suitable method for their solutions. Classical methods are usually problem specific and depend on a certain set of rules to be followed before these methods can be applied. For example, Newton's type methods can be applied only to differentiable functions; likewise, simplex method can be applied only to problems which are strictly linear in nature and so on.

Consequently, in the past few decades, emphasis is being laid on techniques which are generic in nature and can be applied to a wide range of problems. Past few decades have witnessed the emergence of optimization techniques following based on some natural phenomena like theory of evolution or socio cooperative behavior displayed by various species including humans. These are stochastic search techniques and are collectively called nature-inspired metaheuristics (NIM).

In the present article, the search technique taken is firefly algorithm (FA), a comparatively newer addition to the class of NIM. FA belongs to a class of swarm intelligence (SI)-based algorithms. SI takes inspiration from the collective behavior of insects or animals. This term was first used by Beni and Wang [13] in 1989. SI is mainly based on the philosophy that by working together, species can solve the most complex task (e.g., mound building of termites). Various species follow simple interaction rules which they follow for communication and thus form a self-organized multi-agent system. A relation between SI-based algorithms, bio-inspired algorithms, and nature-inspired algorithms can be given as follows:

$$\text{SI-based} \subset \text{bio-inspired} \subset \text{nature-inspired}$$

SI-based $\subset$ bio-inspired $\subset$ nature-inspired

Most common swarm intelligence optimization techniques available in nature include particle swarm optimization (PSO) [14, 15], ant colony optimization (ACO) [16], artificial bee colony (ABC) [17, 18], firefly algorithm (FA) [19, 20], differential evolution (DE) [21, 22], bat algorithm [23], glow swarms [24], krill herd bio-inspired algorithms [25], cuckoo search [26], fish optimization [27], bacterial foraging optimization [28]; most of these algorithms are population based and have a natural advantage over single-point search algorithms [29].

The objective of the present study is to introduce the researchers with a brief overview of FA. The article consists of five sections including introduction. In the second section, we define the working, structure of firefly. In the third section, we classify the firefly algorithm. In the fourth section, we discuss the application of firefly algorithm, and the fifth section is for conclusion.

2   Introduction of Firefly Algorithm

A firefly algorithm was developed by Yang [19]. Fireflies are quite fascinating insects found typically in warm environment and are normally active during night when they look mesmerizing. Some interesting facts about fireflies are as follows:

- More than two thousand species of firefly can be found in nature, and mostly all fireflies produce tiny, periodic flashes. The pattern of flashing is incomparable for a particular species.
- The function of flashing light is either to attract partners (communication) or is a warning toward the predator.
- Each firefly can glow with a different intensity.

Many researchers have discussed firefly behavior in nature. For reference, the interested reader may see [30–32].

In FA algorithm, better fireflies have a smaller error and have a higher intensity. The flashing light can be expressed in such a way that it can be linked with the objective function which is to be optimized. In this paper, firstly, we discuss the structure of the firefly algorithm (FA), classification, and then move toward their applications.

The basic idea of FA is that a firefly will be attracted to any other firefly that has a higher intensity, and that attractiveness (the distance moved toward a more intense firefly) is stronger if the distance between the two fireflies is smaller. Firefly algorithm is based on a physical formulation of light intensity, which is varied at the distance from the eyes of beholder. In general, as the distance between two fireflies' increases, then light intensity decreases rapidly which means light intensity is inversely proportional to the distance between two fireflies [19].

The two major issues in FA are intensity and attractiveness. Since FA is a metaheuristic, one is free to define intensity in any manner while keeping in mind that higher intensity is associated with a better solution/position. The next major issue is to define attractiveness so that closer fireflies will move toward a more intense target. Thus, the brightness phenomenon is associated with objective function to be optimized.

Firefly algorithms use the following three idealized rules:

1. Fireflies are unisex so that they are attracted to each other regardless of their gender.
2. The attractiveness is proportional to the brightness, and both attraction and brightness decrease as the distance between consecutive fireflies increases. This implies that the firefly having lesser brightness will move toward the brighter firefly. However, if the brightness is same, the firefly will have a random movement.
3. For a maximization problem, brightness is proportional to the objective function.

2.1 Structure of Firefly

As already mentioned, in FA, there are two important parameters, intensity and attractiveness. A firefly will move toward the other firefly which is brighter than itself and the attractiveness depends on light intensity.

The light intensity and attractiveness both are inversely proportional to the distance d between attracted fireflies which implies that light intensity and attractiveness decrease as the value of d increases. These two parameters are defined below.

Intensity:

$$I = I_0 * e^{-\gamma d^2},$$

where

I light intensity
I_0 original light intensity or initial light intensity
D distance between firefly i and j
λ the light absorption coefficient controls the light intensity

Attractiveness

Attractiveness is proportional to the light intensity, and attractiveness β is defined as follows:

$$\beta = \beta_0 * e^{-\gamma d^2},$$

where

B_0 attractiveness when d equals to zero

The distance between two fireflies can be defined as follows:

$$d_{ij} = \left\| u_i - u_j \right\| = \sqrt{\sum_{k=1}^{n} \left(u_{i,k} - u_{j,k} \right)^2}.$$

Movement of firefly:

When a firefly i is attracted toward the brighter firefly j, its movement is defined as follows:

$$u_i^{t+1} = u_i^t + \beta_0 * e^{-\gamma d_{i,j}^2} * \left(u_j^t - u_i^t \right) + \alpha * \varepsilon_i.$$

The second term shows attraction, and γ is limitation. If γ tends to zero or is too small, then attractiveness and brightness become constant, $\beta = \beta_0$ implies that a firefly can be seen in any place, and this shows the firefly will also search global firefly. If γ tends to infinity or too large then attractiveness and brightness will

decreases near to zero which means firefly will move randomly and the third term is for randomization here α is a parameter called random parameter.

ε_i can be replaced by (rand − 1/2), where rand is a random number generated between 0 and 1.

The pseudocode of basic FA is given below:

3   Classification

Many variants in firefly algorithms have been proposed in the literature. Attempts have been made to find the best possible combination of parameters through tuning [33] or by controlling the parameters adaptively.

Research has also been done on the movement of fireflies using different probability distributions Levy, uniform, Gaussian etc. or by using chaotic sequences. Binary and real coded, both versions of FA, are available in the literature. In general, more than 20 variants of firefly exist in the literature. Fig. 1 gives a pictorial representation of modified and hybridized variants of FA, while Tables 1 and 2 list the various modified and hybridized FA (Fig. 2).

Begin FA
Define objective function $f(x)$, where $x = (x_i, , , , x_n)$
Generate an initial population
Define I, the light intensity
Define γ, absorption coefficient
While$(t < Max\_Generation)$
For$i = 1\ to\ n(all\ n\ fireflies)$
      For$j = 1\ to\ n(all\ n\ fireflies)$
            If$(I_i > I_j)$, move firefly i towards firefly j
            End if
            Evaluate new solutions and update light intensity;
      End for$j$
End for$i$
Rank the fireflies and find the current best
End while
End FA

Fig. 1 Pseudocode of basic FA

Table 1 Modified firefly algorithms

Topic	References
Elitist FA	[57]
Quaternion FA	[58]
Lévy flights randomized FA	[1, 59]
Gaussian randomized FA	[1, 2]
Harmonic clustering	[60]
Multi-population	[61]
Parallel firefly algorithm	[62]
Chaos randomized FA	[63]
Binary represented FA	[64]

Table 2 Hybrid firefly algorithms

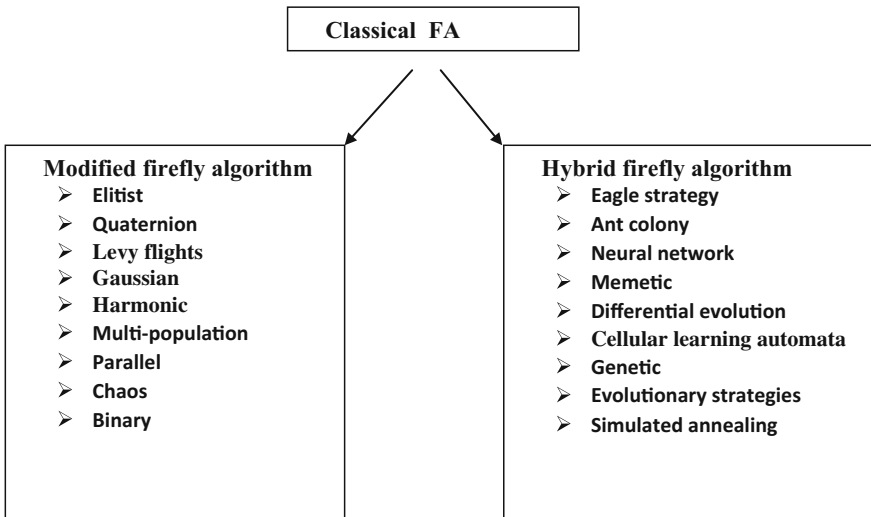| Topic	References
Eagle strategy using Lévy walk	[65]
Ant colony	[66]
Neural network	[67]
Memetic algorithm	[5]
Differential evolution	[68]
Cellular learning automata	[69]
Genetic algorithm	[70]
Evolutionary strategies	[71]
Simulated annealing	[72]

Fig. 2 Classification of firefly algorithm

4 Application

FA has been applied to several fields like economic emissions load dispatch problem, multi-level thresholding selection [34], vector quantization for image compression [35], finding optimal test sequence generation [36], object tracking [37]. Various optimization problems that have been dealt with FA are (Fig. 3) as follows:

- Continuous,
- Constrained,
- Combinatorial,
- Multimodal,
- Multi-objective,
- Dynamic and noisy.
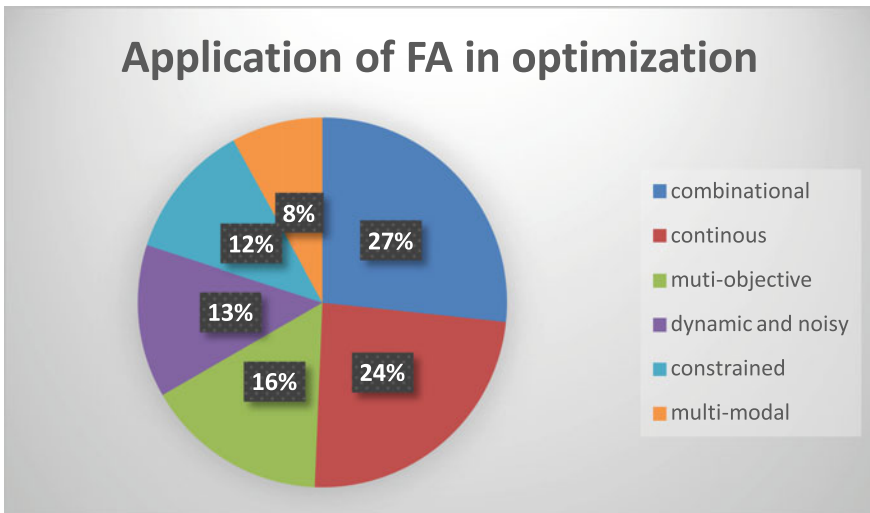
Pie-chart. Uses FA in optimization

Firefly algorithms have also been applied to various real-life applications problems like industrial optimization [38–40], image processing [35, 41], business optimization [42], antenna design [43], civil engineering [44], semantic web [45], robotics [46], chemistry [47], meteorology [48] and wireless sensor networks [49]; optimal placement and sizing of voltage-controlled distributed generators in unbalanced distribution networks [50], rescheduling of real power for congestion management with integration of pumped storage hydro-unit [51], for multi-stage transmission expansion planning with adequacy-security considerations in deregulated environments [52], optimizing real power loss and voltage stability limit of a large transmission network [53], for congestion management in deregulated environment [54].
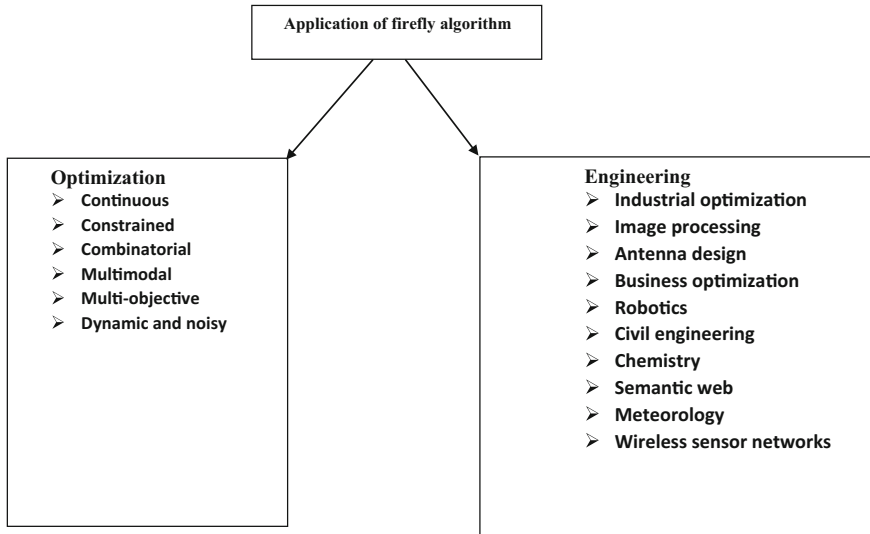
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                        │ Application of firefly algorithm │
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Optimization	Engineering
➢ Continuous	➢ Industrial optimization
➢ Constrained	➢ Image processing
➢ Combinatorial	➢ Antenna design
➢ Multimodal	➢ Business optimization
➢ Multi-objective	➢ Robotics
➢ Dynamic and noisy	➢ Civil engineering
	➢ Chemistry
	➢ Semantic web
	➢ Meteorology
	➢ Wireless sensor networks

Fig. 3 Taxonomy of firefly algorithm

5   Conclusion

The objective of the present study is to familiarize the researchers toward FA, a comparatively newer NIM. The authors have tried to include most of the work proposed in the area of FA; however, it is possible that some important paper is left out. Concluding remarks on FA can be as follows:

- FA has emerged as an attractive alternative for solving complex problems. In a small span of around 6 years, we can find around 20 variants of FA in the literature, including hybridization, variation in parameters.
- FA has been applied to a wide range of optimization problems with highest applications found in combinatorial optimization (27%), followed by continuous optimization (24%). FA has also been applied to multi-objective, noisy, and dynamic optimization problems as well.
- FA has also been applied to different real-life problems like image processing, robotics, business optimization.
- FA can be combined with other soft computing techniques (such as neural network [55], genetic algorithm [56] and other NIAs [14–29]) to get better performance.

References

1. Yang, X.S.: Metaheuristic optimization: algorithm analysis and open problems. In: Pardalos, P.M., Rebennack, S. (eds.) Experimental Algorithms, vol. 6630, pp. 21–32. Lecture Notes in Computer Science. Springer, Berlin (2011)
2. Farahani, S.M., Abshouri, A.A., Nasiri, B., Meybodi, M.R.: A gaussian firefly algorithm. Int. J. Mach. Learn. Comput. **1**(5), 448–454 (2011)
3. Gomes, H.M.: A firefly metaheuristic structural size and shape optimisation with natural frequency constraints. Int. J. Metaheuristics **2**(1), 38–55 (2012)
4. Łukasik, S., Zak, S.: Firefly algorithm for continuous constrained optimization tasks. In: Computational Collective Intelligence. Semantic Web, Social Networks and Multiagent Systems, pp. 97–106. Springer, Berlin (2009)
5. Fister, I., Jr., Yang, X.-S., Fister, I., Brest, J.: Memetic Firefly Algorithm for Combinatorial Optimization, pp. 75–86. Jožef Stefan Institute (2012)
6. Jati, G.: Evolutionary discrete firefly algorithm for travelling salesman problem. In: Adaptive and Intelligent Systems, pp. 393–403 (2011)
7. Khadwilard, A., Chansombat, S., Thepphakorn, T., Thapatsuwan, P., Chainate, W., Pongcharoen, P.: Application of firefly algorithm and its parameter setting for job shop scheduling. In: 1st Symposium on Hands-On Research and, Development, pp. 1–10 (2011)
8. Kwiecień, J., Filipowicz, B.: Firefly algorithm in optimization of queueing systems. Tech. Sci. **60**(2), 363–368 (2012)
9. Miguel, L.F.F., Lopez, R.H., Miguel, L.F.F.: Multimodal size, shape, and topology optimisation of truss structures using the firefly algorithm. Adv. Eng. Softw. **56**, 23–37 (2013)
10. Abedinia, O., Amjady, N., Naderi, M.S.: Multi-objective environmental/economic dispatch using firefly technique. In: 11th International Conference on Environment and Electrical Engineering (EEEIC), pp. 461–466. IEEE (2012)
11. Amiri, B.K, Hossain, L., Crawford, J.W., Wigand, R.T.: Community detection in complex networks: Multi-objective enhanced firefly algorithm. Knowl. Based Syst. **46**, 1–11 (2013)
12. Abshouri, A.A., Meybodi, M.R., Bakhtiary, A.: New firefly algorithm based on multi swarm & learning automata in dynamic environments. In: IEEE proceedings, pp. 73–77 (2011)
13. Beni, G., Wang, J.: Swarm intelligence in cellular robotic systems. In: Proceedings of NATO Advanced Workshop on Robots and Biological Systems, Tuscany, Italy, pp. 26–30 (1989)
14. Kennedy, J., Eberhart, R.: The particle swarm optimization: Social adaptation in information processing. In: Corne, D., Dorigo, M., Glover, F. (eds.) New Ideas in Optimization, pp. 379–387. McGraw Hill, London (1999)
15. Ansari, I.A., Pant, M., Ahn, C.W., Jeong, J.: PSO optimized multipurpose image watermarking using SVD and chaotic sequence. bio-inspired computing-theories and applications. In: Proceedings of the 10th International Conference, BIC-TA 2015 Hefei, China, vol. 562, 25–28 Sept 2015. Springer, Berlin (2016)
16. Dorigo, M., Di Caro, G.: The ant colony optimization meta-heuristic. In: Corne, D., Dorigo, M., Glover, F. (eds.) New Ideas in Optimization, pp. 11–32. McGraw-Hill, London (1999)
17. Karaboga, D., Basturk, B.: A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. J. Global Optim. **39**(3), 459–471 (2007)
18. Ansari, I.A., Pant, M., Ahn, C.W.: ABC optimized secured image watermarking scheme to find out the rightful ownership. Optik-Int. J. Light Electron Opt. **127**(14), 5711–5721 (2016)
19. Yang, X.S.: Fire fly algorithm. Nat. Inspir. Metaheuristic Algorithms 79–90 (2008)
20. Gandomi, A., Yang, X.-S., Talatahari, S., Alavi, A.: Metaheuristic in modeling and optimization. In: Structures and Infrastructures, pp. 1–24. Elsevier, Waltham (2013)
21. Jauhar, S.K., Pant, M., Deep, A.: An approach to solve multi-criteria supplier selection while considering environmental aspects using differential evolution. In: International Conference on Swarm, Evolutionary, and Memetic Computing, pp. 199–208. Springer, Berlin (2013)

22. Kumar Jauhar, S., Pant, M., Nagar, M.C.: Differential evolution for sustainable supplier selection in pulp and paper industry: a DEA based approach. Comput. Methods Mater. Sci. **15** (2015)
23. Yang, X.S.: A new metaheuristic bat-inspired algorithm. In: Cruz, C., Gonzlez, J., Krasnogor, G.T.N., Pelta, D.A. (eds.) Nature Inspired Cooperative Strategies for Optimization (NISCO 2010), Studies in Computational Inteligence, vol. 284, pp. 65–74. Springer, Berlin (2010)
24. Krishnanand, K.N., Ghose, D.: Glowworm swarm optimization for simultaneous capture of multiple local optima of multimodal functions. Swarm intell. **3**(2) 87–124 (2009)
25. Gandomi, A.H., Alavi, A.H.: Krill herd: a new bio-inspired optimization algorithm. Commun. Nonlinear Sci. Numer. Simul. **17**(12) 4831–4845 (2012). doi:10.1016/j.cnsns.2012.05.010
26. Yang, X.S., Deb, S.: Cuckoo search via levy flights. In: World Congress on Nature & Biologically Inspired Computing (NaBIC 2009), IEEE Publications, pp. 210–214 (2009)
27. Li, X.-L., Qian, J.-X.: Studies on artificial fish swarm optimization algorithm based on decomposition and coordination techniques. J. Circuits Syst. **1**, 1–6 (2003)
28. Passino, K.M.: Bacterial foraging optimization. Innov. Dev. Swarm Intell. Appl. 219–233 (2012)
29. Prugel-Bennett, A.: Benefits of a population: five mechanisms that advantage population-based algorithms. IEEE Trans. Evol. Comput. **14**(4), 500–517 (2010)
30. Brasier, A., Tate, J., Habener, J., et al.: Optimized use of the firefly Luciferase assay as a reporter gene in mammalian cell lines. BioTechniques **7**(10), 11–16 (1989)
31. Strehler, B.L., Totter, J.R.: Fire fly luminescence in the study of energy transfer mechanisms. I. Substrate and enzyme determination. Arch. Biochem. Biophys. **40**(1), 28–41 (1952)
32. Deluca, M.: Firefly luciferase. Adv. Enzymol. Relat. Areas Mol. Biol. **40**, 37–68 (2006)
33. Eiben, A., Smit, S.: Parameter tuning for configuring and analysing evolutionary algorithms. Swarm Evol. Comput. **1**(1), 19–31 (2011)
34. Apostolopoulos, T., Vlachos, A.: Application of the firefly algorithm for solving the economic emissions load dispatch problem. Int. J. Comb. **2011** (2010)
35. Horng, M.-H.: Vector quantization using the firefly algorithm for image compression. Expert Syst. Appl. **39**(1), 1078–1091 (2012)
36. Srivstava, P.R., Mallikarjun, B., Yang, X.-S.: Optimal test sequence generation using firefly algorithm. Swarm Evol. Comput. **8**, 44–53 (2013)
37. Gao, M.-L., et al.: Object tracking using firefly algorithm. IET Comput. Vis. **7**(4), 227–237 (2013)
38. Yang, X.S., Hosseini, S.S.S., Gandomi, A.H.: Firefly algorithm for solvingnon-convex economic dispatch problems with valve loading effect. Appl. Soft Comput. **12**(3), 1180–1186 (2011)
39. Mauder, T., Sandera, C., Stetina, J., Seda, M.: Optimization of the quality of continuously cast steel slabs using the firefly algorithm. Mater. Tehnol. **45**(4), 347–350 (2011)
40. Chatterjee, A., Mahanti, G., Chatterjee, A.: Design of a fully digital controlled reconfigurable switched beam concentric ring array antenna using firefly and particle swarm optimization algorithm. Prog. Electromagnet. Res. B **36**, 113–131 (2012)
41. Horng, M., Jiang, T.: The codebook design of image vector quantization based on the firefly algorithm. Comput. Collect. Intell. Technol. Appl. 438–447 (2010)
42. Yang, X.-S., Deb, S., Fong, S.: Accelerated particle swarm optimization and support vector machine for business optimization and applications. In: International Conference on Networked Digital Technologies, Springer, Berlin (2011)
43. Basu, Banani, Mahanti, Gautam Kumar: Fire fly and artificial bees colony algorithm for synthesis of scanned and broadside linear array antenna. Prog. Electromagnet. Res. B **32**, 169–190 (2011)
44. Gholizadeh, S., Barati, H.: A comparative study of three metaheuristics for optimum design of trusses. Int. J. Optim. Civil Eng. **3**(3), 423–441 (2012)
45. Pop, C.B., et al.: A hybrid firefly-inspired approach for optimal semantic web service composition. Scalable Comput. Pract. Exp. **12**(3), 363–370 (2011)

46. Severin, S., Rossmann, J.: A comparison of different metaheuristic algorithms for optimizing blended PTP movements for industrial robots. In: International Conference on Intelligent Robotics and Applications. Springer, Berlin (2012)
47. Fateen, S.E.K., Bonilla-Petriciolet, A., Rangaiah, G.P.: Evaluation of covariance matrix adaptation evolution strategy, shuffled complex evolution and firefly algorithms for phase stability, phase equilibrium and chemical equilibrium problems. Chem. Eng. Res. Des. **90** (12), 2051–2071 (2012)
48. Santos, A.F.D, et al.: Firefly optimization to determine the precipitation field on South America. Inverse Prob. Sci. Eng. **21**(3), 451–466 (2013)
49. Breza, M., McCann, J.A.: Lessons in implementing bio-inspired algorithms on wireless sensor networks. NASA/ESA Conference on Adaptive Hardware and Systems. AHS'08. IEEE (2008)
50. Othman, M.M., et al.: Optimal placement and sizing of voltage controlled distributed generators in unbalanced distribution networks using supervised firefly algorithm. Int. J. Electr. Power Energy Syst. **82**, 105–113 (2016)
51. Gope, S., et al.: Rescheduling of real power for congestion management with integration of pumped storage hydro unit using firefly algorithm. Int. J. Electr. Power Energy Syst. **83**, 434–442 (2016)
52. Rastgou, A., Moshtagh, J.: Application of firefly algorithm for multi-stage transmission expansion planning with adequacy-security considerations in deregulated environments. Appl. Soft Comput. **41**, 373–389 (2016)
53. Balachennaiah, P., Suryakalavathi, M., Nagendra, Palukuru: Optimizing real power loss and voltage stability limit of a large transmission network using firefly algorithm. Eng. Sci. Technol. Int J **19**(2), 800–810 (2016)
54. Verma, S., Mukherjee, V.: Firefly algorithm for congestion management in deregulated environment. Eng. Sci. Technol. Int. J. (2016)
55. Ansari, I.A., Singla, R.: BCI: an optimised speller using SSVEP. Int. J. Biomed. Eng. Technol. **22**(1), 31–46 (2016)
56. Jauhar, S.K., Pant, M.: Genetic algorithms in supply chain management: a critical analysis of the literature. Sādhanā **41**(9), 993–1017 (2016)
57. Ong, H.C., Tilahun, S.L.: Modified firefly algorithm. J. Appl. Math. **2012**, 12 (2012)
58. Fister, I., Yang, X.-S., Brest, J., Fister Jr., I.: Modified firefly algoirthm using quaternion representation. Expert Syst. Appl. (2013). doi:10.1016/j.eswa.2013.06.070
59. Yang, X.S.: Efficiency analysis of swarm intelligence and randomization techniques. J. Comput. Theor. Nanosci. **9**(2), 189–198 (2012)
60. Adaniya, M.H.A.C., Lima, F.M., Rodrigues, J.J.P.C., Abrao, T., Proenca, M.L.: Anomaly detection using DSNS and firefly harmonic clustering algorithm. In: IEEE International Conference on Communications (ICC), pp. 1183–1187. IEEE (2012)
61. Liu, G.: A multipopulation firefly algorithm for correlated data routing in underwater wireless sensor networks. Int. J. Distrib. Sens., Netw (2013)
62. Husselmann, A.V., Hawick, K.A.: Parallel parametric optimisation with firefly algorithms on graphical processing units. Technical Report CSTN-141 (2012)
63. Gandomi, A.H., Yang, X.-S., Talatahari, S., Alavi, A.H.: Firefly algorithm with chaos. Commun. Nonlinear Sci. Numer. Simul. **18**(1), 89–98 (2013)
64. Chandrasekaran, K., Simon, S.P., Padhy, N.P.: Binary real coded firefly algorithm for solving unit commitment problem. Inf. Sci. (2013). doi:10.1016/j.ins.2013.06.022
65. Yang, X.S., Deb, S.: Eagle strategy using levy walk and firefly algorithms for stochastic optimization. In: Nature Inspired Cooperative Strategies for Optimization (NICSO 2010), pp. 101–111 (2010)
66. Aruchamy, R., Vasantha, K.D.D.: A comparative performance study on hybrid swarm model for micro array data. Int. J. Comput. Appl. **30**(6), 10–14 (2011)
67. Hassanzadeh, T., Faez, K., Seyfi, G.: A speech recognition system based on structure equivalent fuzzy neural network trained by firefly algorithm. In: International Conference on Biomedical Engineering (ICoBE), pp. 63–67. IEEE (2012)

68. Abdullah, A., Deris, S., Mohamad, M., Hashim, S.: Anewhybrid firefly algorithm for complex and nonlinear problem. In: Omatu, S., et al. (eds.) Distributed Computing and Artificial Intelligence, vol. 151, pp. 673–680. Springer, Berlin (2012)
69. Hassanzadeh, T., Meybodi, M.R.: A new hybrid algorithm based on firefly algorithm and cellular learning automata. In: 20th Iranian Conference on Electrical Engineering, pp. 628–633. IEEE (2012)
70. Luthra, J., Pal, S.K.: A hybrid firefly algorithm using genetic operators for the crypt analysis of a monoalphabetic substitution cipher. In: World Congress on Information and Communication Technologies (WICT), pp. 202–206. IEEE (2011)
71. LulesegedTilahun, S., Ong, H.C.: Vector optimisation using fuzzy preference in evolutionary strategy based firefly algorithm. Int. J. Oper. Res. **16**(1), 81–95 (2013)
72. Vahedi Nouri, B., Fattahi, P., Ramezanian, R.: Hybrid firefly-simulated annealing algorithm for the flow shop problem with learning effects and flexible maintenance activities. Int. J. Prod. Res. (ahead-of-print), 1–15 (2013)