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REVIEW

Dragonfly algorithm: a comprehensive review and applications

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Abstract

Dragonfly algorithm (DA) is a novel swarm intelligence meta-heuristic optimization algorithm inspired by the dynamic and static swarming behaviors of artificial dragonflies in nature. It has proved its effectiveness and superiority compared to several well-known meta-heuristics available in the literature. This paper presents a comprehensive review of DA and its new variants classified into modified and hybrid versions. It also describes the main diverse applications of DA in several fields and areas such as machine learning, neural network, image processing, robotics, and engineering. Finally, the paper suggests some possible interesting research on the applications and hybridizations of DA for future works.

Keywords Dragonfly algorithm · Nature-inspired algorithm · Swarm intelligence · Meta-heuristics

1 Introduction

Meta-heuristics are approximate optimization algorithms that have attracted great interest from many researchers in several fields such as computer science, operation research, bio-informatics, and engineering. This interest is due to their simplicity, flexibility, and robustness to solve a variety of optimization problems in a reasonable time.

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According to Fister et al. [1], meta-heuristics can be divided into two categories: non-nature-inspired meta-heuristics and nature-inspired meta-heuristics.

Nature-inspired meta-heuristic algorithms can be classified into five main categories: evolutionary-based, physics-based, chemistry-based, human-based, and swarm intelligence-based.

Evolutionary algorithms are inspired by the concept of biological evolution in nature using the operators of selection, crossover, mutation, and reproduction to find better candidate solutions. Genetic algorithm (GA) [2], developed by Holland in 1992, is regarded as the best evolutionary algorithm. Some other popular evolutionary algorithms are: differential evolution (DE) [3], evolutionary programming (EP) [4], evolution strategy (ES) [5], genetic programming (GP) [6], probability-based incremental learning (PBIL) [7], and biogeography-based optimizer (BBO) [8, 9].

The second category of nature-inspired meta-heuristic algorithms includes physics-based algorithms. These optimization algorithms mimic physical rules in the universe. Some of the popular physics-based algorithms are: simulated annealing (SA) [10], central force optimization (CFO) [11–13], gravitational search algorithm (GSA) [14, 15], and Big Bang–Big Crunch (BBBC) [16]. Other recently developed physics-based algorithms are: electromagnetic field optimization (EFO) [17], water evaporation optimization (WEO [18], optics-inspired optimization (OIO) [19], multi-verse optimizer (MVO) [20], thermal exchange optimization

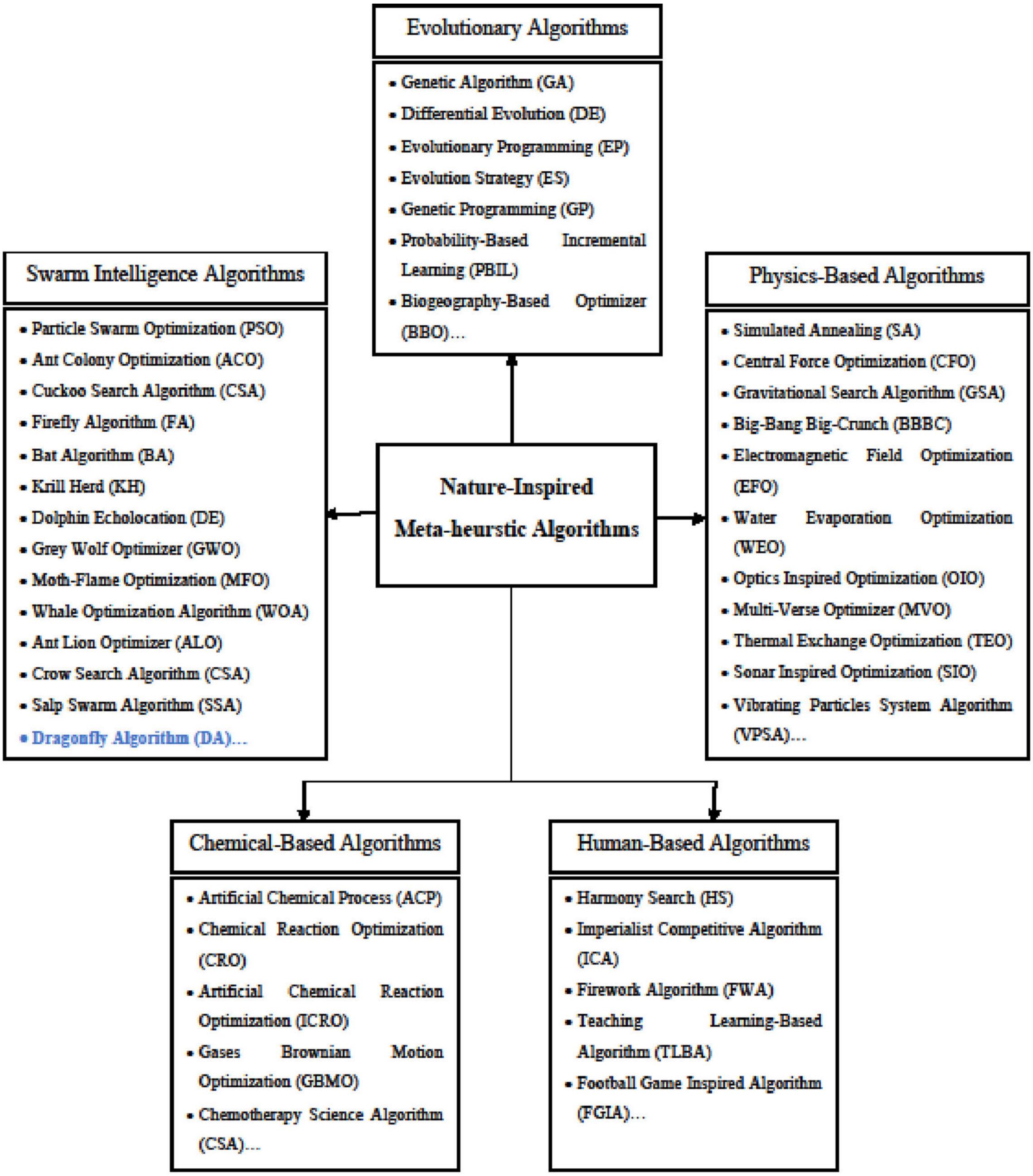

Fig. 1 Classification of nature-inspired meta-heuristic algorithms

(TEO) [21], sonar-inspired optimization (SIO) [22], and vibrating particles system algorithm (VPSA) [23].

The third category is chemistry-based algorithms that imitate chemical rules. Some of the most well-known chemistry-based algorithms are: artificial chemical process (ACP) [24], chemical reaction optimization (CRO) [25], artificial chemical reaction optimization (ACRO) [26], gases Brownian motion optimization (GBMO) [27], and chemotherapy science algorithm (CSA) [28].

The fourth category is human-based algorithms that are inspired from several phenomena commonly associated with the behaviors and the perception of human beings [29]. Some of the most well-known human-based algorithms are: harmony search (HS) [30], imperialist competitive algorithm (ICA) [31], firework algorithm (FWA) [32], teaching–learning-based algorithm (TLBA) [33], and football game-inspired algorithm (FGIA) [34].

The fifth and last category includes swarm intelligence (SI) optimization algorithms. These algorithms are inspired from the collective social behavior of swarms or systems or communities such as herds of animals, schools of fish, colonies of insects, and flocks of birds. The two most

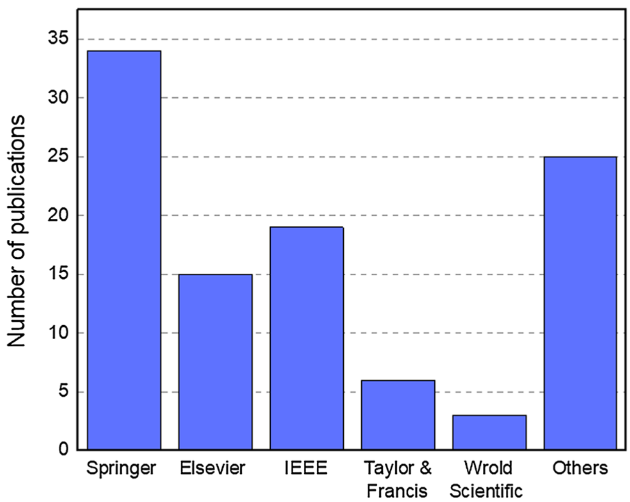

Fig. 2 Number of related publications of DA by scientific databases

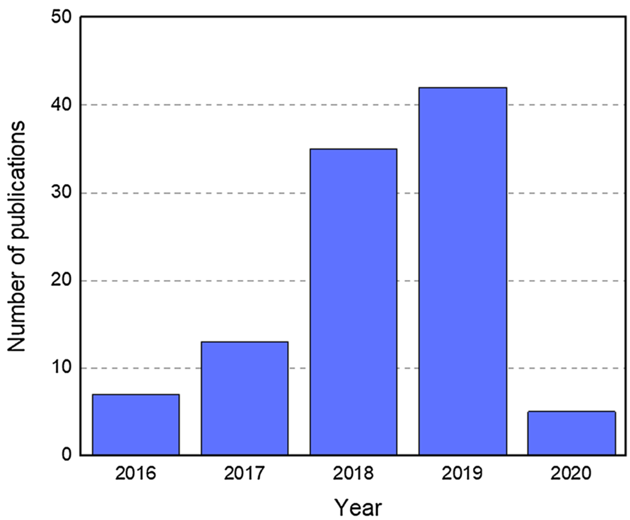

Fig. 3 Number of DA-related publications per year

popular SI algorithms are particle swarm optimization (PSO) [35, 36] and ant colony optimization (ACO) [37, 38]. Other SI optimization algorithms are: cuckoo search algorithm (CS) [39], firefly algorithm (FA) [40–42], bat algorithm (BA) [43, 44], krill herd (KH) [45, 46], dolphin echolocation (DE) [47], grey wolf optimizer (GWO) [48, 49], moth-flame optimization (MFO) algorithm [50], whale optimization algorithm (WOA) [51], ant lion optimizer (ALO) [52], crow search algorithm (CSA) [53], salp swarm algorithm (SSA) [54], dragonfly algorithm (DA) [55], and many others. Figure 1 shows the general classification of nature-inspired meta-heuristic algorithms.

DA is one of the recent swarm intelligence optimization algorithms that was introduced by Mirjalili [55] in 2016. It is used to solve a large variety of different optimization problems such as image processing, robotics, medical, computer science, engineering, and many others. DA is inspired from the natural behavior of the artificial dragonflies and showed its effectiveness and robustness compared to several well-regarded optimization algorithms existing in the literature. Similar to other SI, DA has some advantages such as [56]:

- Few control parameters as compared to EA.
- The information about the position of the individuals can be maintained at the time of iterations.
- Memory space is less utilized by SI compared to EA.

However, DA has lower probability to trap into local optima as compared to other algorithms. This paper presents a review of DA, its variants, and its applications in different areas. The review considers various well-known databases such as Springer, Elsevier, IEEE, Taylor & Francis, World Scientific, and others. Figure 2 shows the number of related publications ranked by scientific databases. Figure 3 shows the distribution of DA publications by year. Table 1 presents the top ten countries ranked by the number of DA publications. The top ten DA-related keywords are presented in Table 2. As it is illustrated in these figures and tables, the interest on the study of DA has

Table 1 Top ten countries ranked by the number of DA-related publications

Country	Rank	Number of publications
India	1	51
China	2	16
Egypt	3	6
Algeria	4	4
Iran	5	4
Jordan	6	3
Palestine	7	3
Germany	8	2
Turkey	9	2
Irak	10	2

Table 2 Top ten DA-related keywords

Rank	Keywords	Count
1	Dragonfly algorithm	78
2	Optimization	12
3	Feature selection	8
4	Optimization algorithms	7
5	Particle swarm optimization	6
6	Meta-heuristics	6
7	Support vector machine	5
8	Neural network	5
9	Swarm intelligence	4
10	Differential evolution	4

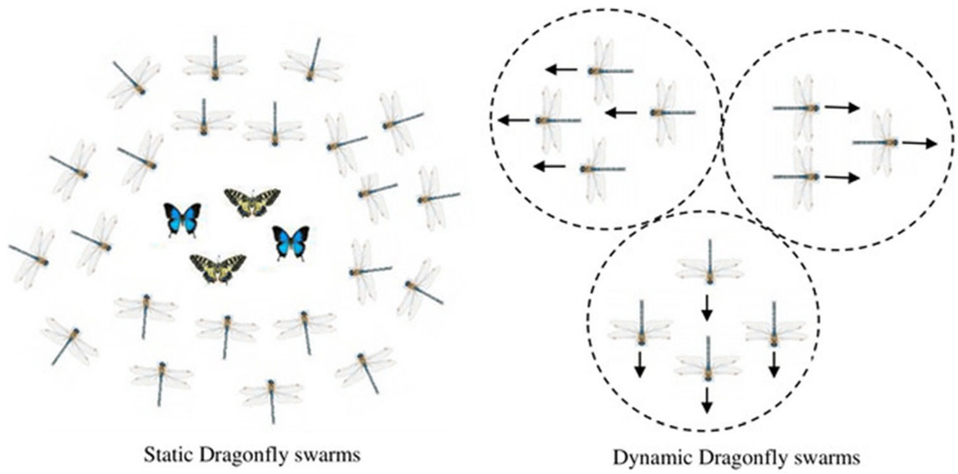

Fig. 4 The static and dynamic swarming behaviors of dragonflies

enormously increased in the last 4 years. Since the introduction of DA in 2016, more than 100 DA-related papers have been published. The number of articles published in Springer is higher than other databases, and 2019 represents the highest use of DA compared to other years.

This paper is organized as follows: Section 2 describes the general structure and the main steps of DA. Section 3 provides a review of recent variants of the original DA. Section 4 gives an extensive overview of the application of DA in several areas. Finally, Sect. 5 concludes the paper and discusses some possible research applications of DA for future works.

2 Dragonfly algorithm

Dragonfly algorithm (DA), developed by Mirjalili in 2016 [55], is a recent and interesting nature-inspired metaheuristic optimization algorithm used to solve a large variety of optimization problems. Dragonflies are small flying carnivorous insects that hunt and eat a wide variety of small insects like butterflies, bees, ants, and mosquitoes [55, 57, 58]. There are 3000 different species of dragonflies, and their life cycle includes two stages called nymph and adult [55, 59]. DA is based on the natural dynamic (migratory) and static (feeding) swarming behaviors of dragonflies [55, 60]. The dynamic and static swarms, illustrated in Fig. 4, constitute the exploitation and exploration phases of DA, respectively. In the exploitation phase, a large number of dragonflies make the swarms migrate in one direction over long distances and distract from enemies. In the exploration phase, however, dragonflies make small groups and fly back and forth over a small area to search for food and attract flying preys.

Five basic primitive principles, presented in Fig. 5, are utilized to model the swarm behaviors of dragonflies as follows [55, 60–62]. In the following equations, P represents the position of the current individual, P_j the position of the jth neighboring individual, and M the number of neighboring individuals

1. *Separation* represents the static collision avoidance that individuals follow to avoid collision with other individuals in the neighborhood; it is mathematically modeled as follows:

$$S_i = -\sum_{j-1}^{M} P - P_j \tag{1}$$

2. *Alignment* indicates the individual's velocity matching between other neighborhood individuals of the same group. The alignment is represented as follows:

$$A_i = \frac{\sum_{j-1}^{M} V_j}{M} \tag{2}$$

where v_j denotes the velocity of the jth individual.

3. *Cohesion* represents the tendency of individuals toward the center of the swarms group. It is defined as follows:

$$C_i = \frac{\sum_{j-1}^{M} P_j}{M} - P \tag{3}$$

4. *Attraction* toward the food source (F) is mathematically modeled by:

$$F_i = F_p - P \tag{4}$$

where F_i represents the food source of the ith individual and F_p is the position of the food source.

5. *Distraction from the enemies* is modeled mathematically by:

$$E_i = E_p + P \tag{5}$$

where E_i denotes the position of the enemy of the ith individual and E_p denotes the enemy's position.

Positions of artificial dragonflies inside their search space are updated considering the step vector ΔP and the position

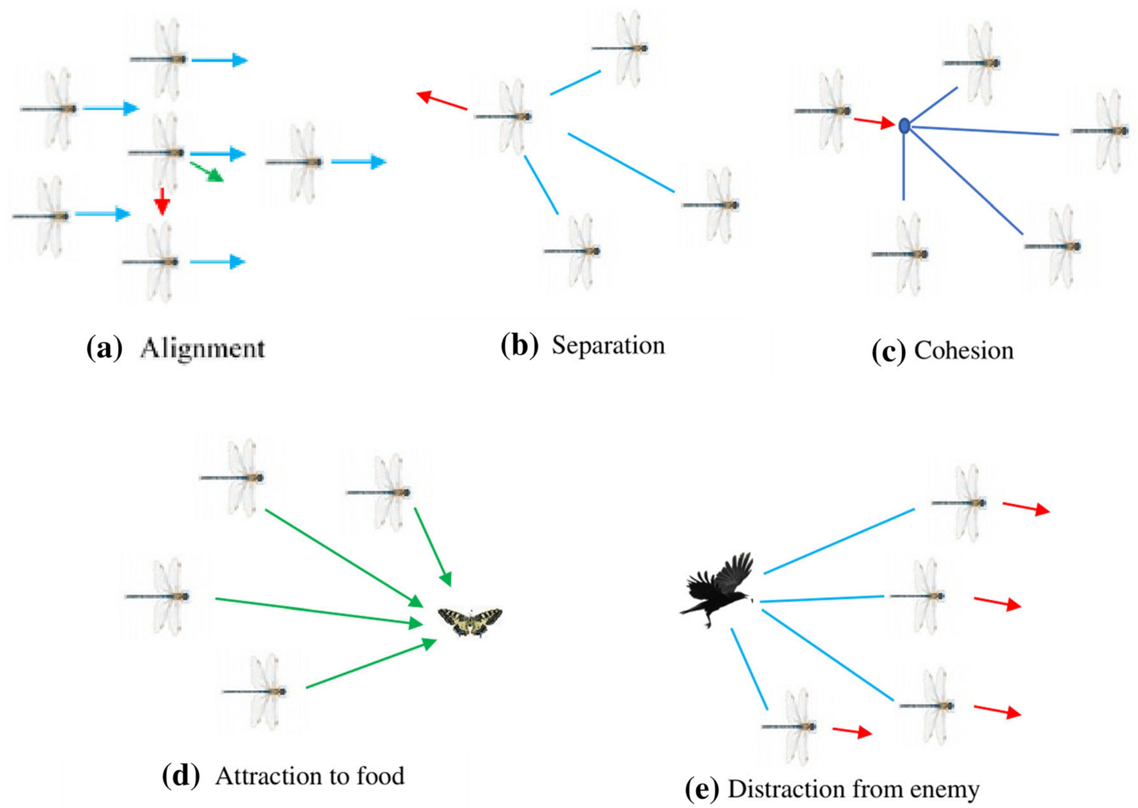

Fig. 5 Primitive corrective patterns between dragonflies in a swarm (different steps of the artificial dragonfly algorithm)

vector P. The step vector ΔP is similar to the velocity vector in PSO algorithm. It is given and updated as follows:

$$\Delta P_i^{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + \omega \Delta P_i^t \quad (6)$$

where s represents the separation weight, S_1 is the separation of the ith individual, a represents the alignment weight, A_i denotes the alignment of the ith individual, c is the cohesion weight, C_i is the cohesion of the ith individual, f represents the food factor, F_i is the food source of the ith individual, e represents the enemy factor, E_i represents the enemy position of the ith individual, w is the inertia weight, and t is the iteration number. Then, the position of the ith dragonfly at $t+1$ is updated as follows:

$$P_i^{t+1} = P_i^t + \Delta P_i^{t+1} \quad (7)$$

The exploration is assured by using high alignment and low cohesion weights; however, the exploitation is assured by using low alignment and high cohesion weights [62]. The convergence rate of DA can be controlled by tuning the weights s, a, c, f, e, and w adaptively. In order to enhance the exploration, the randomness, and the exploitation of the artificial dragonflies, random walk (Levy flight) is introduced when there are no neighboring solutions. Therefore, the position of the ith dragonfly at iteration $t+1$ is updated as follows:

$$P_i^{t+1} = P_i^t + \mathrm{Levy}(d) \times P_i^t \quad (8)$$

where d represents the dimension of the position vectors. Levy flight is calculated by:

$$\mathrm{Levy}(d) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}} \quad (9)$$

where r_1 and r_2 are random vectors uniformly distributed in the range [0,1], β is a constant, and γ σ represents the gamma function. γ is calculated as follows:

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\Pi\beta}{2})}{\Gamma \times 2^{(\frac{\beta-1}{2})} \times \beta \times (\frac{1+\beta}{2})} \right)^{\frac{1}{\beta}} \quad (10)$$

$$\Gamma(a) = \int_0^\infty (t^{a-1} e^{-t}) \mathrm{d}t \quad (11)$$

When a is an integer, we have:

$$\Gamma(a) = (a-1)! \quad (12)$$

Algorithm 1 [55] gives the pseudo-code of the original dragonfly algorithm. Its corresponding flowchart is represented in Fig. 6. The MATLAB code of DA can be downloaded from: http://www.alimirjalili.com/DA_download.html.

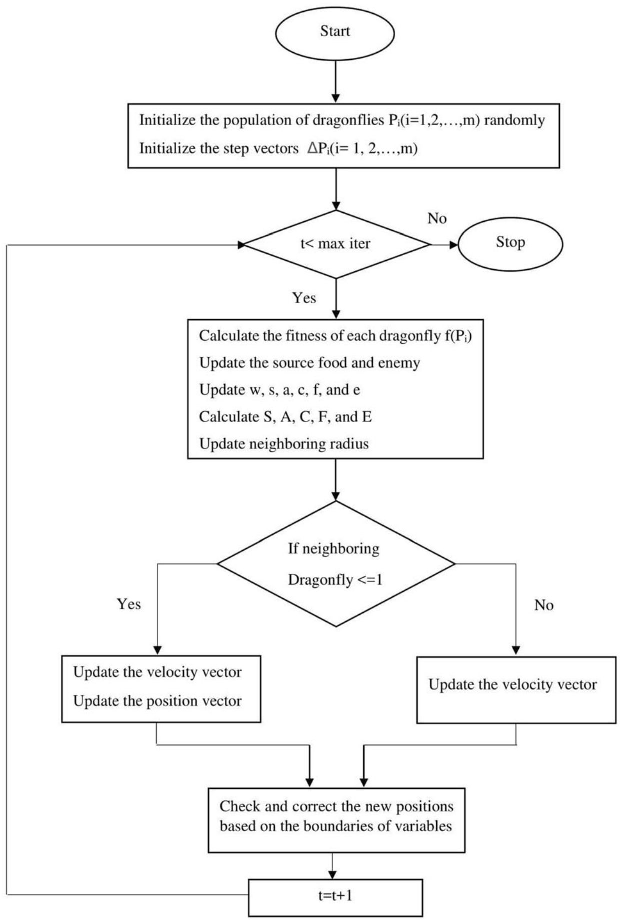

Fig. 6 Flowchart of the dragonfly algorithm

Algorithm 1 The pseudo-code of the Dragonfly Algorithm

Initialize the population of dragonflies $P_i(i = 1, 2, \dots, m)$ randomly
Initialize the step vectors $\Delta P_i(i = 1, 2, \dots, m)$
while $(t < Maximum\ number\ of\ iterations)$ **do**
  Calculate the fitness of each dragonfly $f(P_i)$
  Update the source food and enemy
  Update w, s, a, c, f, and e
  Calculate S, A, C, F, and E using equations (1) to (5)
  Update neighboring radius
  if a dragonfly has at least one neighboring dragonfly **then**
    Update the velocity vector ΔP_i^{t+1} using equation (6)
    Update the position vector P_i^{t+1} using equation (7)
  else
    Update P_i^{t+1} using equation (8)
  end if
  Check and correct the new positions based on the boundaries of variables
end while

3 Recent variants of dragonfly algorithm

A number of recent variants of standard DA have been suggested in order to provide a good balance between exploration and exploitation, increase the diversity of the solutions, and improve the performance of the classical DA. The variants of DA are categorized into modified and hybrid versions. Figure 7 shows these variants as a pie chart. According to the results shown in this figure, modified versions of DA have more percentage compared to hybridization versions.

3.1 Modified versions of dragonfly algorithm

Some recent modified versions of DA are given in Table 3. The details of each modified version are shown below.

3.1.1 Binary dragonfly algorithm

Abdel-Basset et al. [63] presented a binary version of dragonfly algorithm (BDA). BDA is based on V-shaped transfer function for solving the 0–1 knapsack problem (0–1 KP) which is a well-known combinatorial optimization NP-hard problem. Experimental results showed the strong convergence and stability of BDA for solving (0–1 KP) compared to other algorithms existing in the literature.

Sawhney and Jain [64] proposed a modified binary DA for solving feature selection problem. A penalty function was incorporated in the binary DA to enhance the feature selection performance. Simulation results showed the efficiency of the proposed method compared to fuzzy rule-based systems, GA, and random forest classifiers.

Mafarja et al. [65] integrated eight time-varying transfer functions (S-shaped and V-shaped functions) into DA to investigate the impact of the step vector on balancing the exploration and exploitation behavior of BDA. To assess the effectiveness of the proposed approach, the task of feature selection was considered using eighteen benchmark datasets taken from the UCI data repository. Simulation

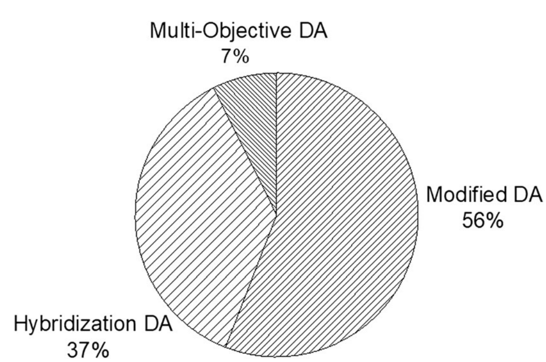

Fig. 7 The variants of DA

Table 3 Modified versions of DA

Name	Research works
Binary dragonfly algorithm	Abdel-Basset et al. [63], Sawhney and Jain [64], Mafarja et al. [65], Abuomar and Al-Aubidy [66]
Chaotic dragonfly algorithm	Sayed et al. [67], Baiche et al. [60]
Adaptive dragonfly algorithm	Sambandam and Jayaraman [68], Jadhav and Joshi [69], Apare and Gujar [70]
Fuzzy-based dragonfly algorithm	Kouba et al. [71]
Elite opposition-based dragonfly algorithm	Peng et al. [72], Song and Li [73]
Clustering-based dragonfly algorithm	Aadil et al. [74], Bhavani et al. [75], Hema et al. [76]
Dragonfly algorithm with support vector machine	Tharwat et al. [77], Elhariri et al. [78], Feng et al. [79], Li et al. [80], Li et al. [81]
Dragonfly algorithm with support vector regression	Li et al. [82], Amroune et al. [57]
Dragonfly algorithm with neural network	Yasen et al. [83], VeeraManickam et al. [84], Chatra et al. [85], Nair and Linda [86]
Multi-objective dragonfly algorithm	Li et al. [87], Khalilpourazari and Khalilpourazary [88], Vikram et al. [89], Weijia et al. [90]
Dragonfly with extreme learning machine	Abdul Salam et al. [91], Wu et al. [92]
Other ameliorated dragonfly algorithms	Sudabattula et al. [93], Kumar et al. [94], Acı and Gulcan [95], Suresh et al. [96], Sugave et al. [97], Mafarja et al. [98], Shelke and Prasad [99], Patil and Atique [100], Yuan et al. [101], Murugaperumal et al. [102]

results showed the superior performance of the proposed approach compared to binary grey wolf algorithm (BGWO), binary gravitational search algorithm (BGSA), binary bat algorithm (BBA), PSO, and GA. Abuomar and Al-Aubidy [66] adopted a binary DA for swarm mobile robots taking into account obstacle avoidance and communication constraints. Simulation results demonstrated the performance of the proposed robotic BDA to obtain an optimal simple solution with a shorter time compared with other rescue algorithms.

3.1.2 Chaotic dragonfly algorithm

Sayed et al. [67] proposed an improved chaotic dragonfly algorithm (CDA) based on the integration of chaos in DA for solving the feature selection problem. The chaotic method was used to adjust the random parameters of DA and accelerate its convergence rate. The performance of CDA was evaluated in comparison with PSO, CSO, GWO, and ABC based on 553 drugs taken from DrugBank database. Experimental results showed the robustness and performance of the proposed algorithm to find the optimal feature subset compared to other existing optimization algorithms.

Baiche et al. [60] proposed an enhanced binary dragonfly algorithm (EBDA) for solving the graph coloring problem. The Gaussian random selection method and chaotic method were introduced into BDA to determine the value of the inertia weight w and the random parameters, respectively. Results showed the performance of the proposed algorithm compared to some well-known metaheuristics in the literature.

3.1.3 Adaptive dragonfly algorithm

Sambandam and Jayaraman [68] proposed a self-adaptive dragonfly algorithm (SADFO) for solving the multilevel segmentation problem. A self-adaptive mechanism was applied to tune the DFO parameters in order to land at the global best solution with minimum execution time. The performance of SADFO was evaluated based on real-life and medical images. Experimental results demonstrated the performance of SADFO to obtain the global best solution.

Jadhav and Joshi [69] proposed a new adaptive dragonfly algorithm (ADF) with test-driven development (TDD) proprieties for model transformation problem. The proposed ADF used an optimal objective function with three UML class diagrams (CLD). Simulation results showed the performance of ADF compared to other existing algorithms such as standard DA, SA, and PSO.

Apare and Gujar [70] proposed an adaptive DA (ADF) for data privacy preservation in Internet of things (IoT).

The performance of ADF was evaluated based on 18 different physical activities. Simulation results demonstrated the effectiveness of ADF compared to GA, PSO, ABC, FA, and DA.

3.1.4 Fuzzy-based dragonfly algorithm

Kouba et al. [71] proposed an optimal combined fuzzy PID controller using DA for solving the automatic generation control (AGC) problem in power systems. The superiority of the proposed method was tested investigating two equal areas of non-reheat thermal power system. Simulation results showed the efficiency of the proposed method and its robustness to improve the frequency regulation loop of linear and nonlinear power systems compared to previous AGC techniques reported in the literature such as GA, PSO, PS, BF, and DE.

3.1.5 Elite opposition-based dragonfly algorithm

Peng et al. [72] proposed a modified DA based on optimal multilevel thresholding to address color image segmentation and determine the optimal thresholds values. Elite opposition-based learning (EOBL) strategy and chaotic map method were used to enhance the randomness of the initial population of DA. The performance of the algorithm was evaluated based on ten color images taken from the Berkley segmentation dataset. Experimental results showed the effectiveness and accuracy of DA compared to nine meta-heuristic algorithms exiting in the literature.

Song and Li [73] proposed an enhanced DA, called EOEDA, based on EOBL strategy and exponential function adaptive step. The authors gave two contributions. The first contribution was the introduction of elite individual to generate the opposite solutions by EOBL; the second contribution was the use of adaptive step with exponential function to replace the original random step. Simulation results showed that EOEDA has faster convergence speed and higher convergence accuracy compared to the standard DA and some other algorithms.

3.1.6 Clustering-based dragonfly algorithm

Aadil et al. [74] proposed a method, called CAVDO, based on DA and clustering algorithm. CAVDO is proposed to construct ideal clustering solution of Internet of vehicle (IoV) routing and ensure the stability of topology. CAVDO was compared with comprehensive learning particle swarm optimization (CLPSO) and progressive baseline techniques ant colony optimization (PBTACO) algorithms. Simulation results demonstrated that CAVDO gives a minimum number of clusters according to current channel condition in many cases compared to CLPSO and PBTACO.

Bhavani et al. [75] proposed an efficient clustering method based on the combination of DA with tri-level ontology construction model for solving fair semantic web content retrieval. The performance of the proposed method was evaluated based on human diseases datasets in the dimension of 757×9. Simulation results showed the performance of the proposed clustering method compared to the well-known clustering approaches existing in the literature in terms of surfing time and retrieval accuracy.

Hema et al. [76] proposed a DA-based clustering protocol (DCP) to enhance the data transmission in radio frequency identification (RFID) networks. Simulation results demonstrated the performance of the proposed algorithm compared to FA and LEACH algorithm in terms of residual energy, lifetime, and the number of packets sent to the base station.

3.1.7 Dragonfly algorithm with support vector machine

Tharwat et al. [77] proposed a combined method based on DA and support vector machine (SVM), called DA-SVM, for optimizing the SVM parameters and decreasing classification error. DA-SVM was tested using six datasets obtained from the UCI machine learning data repository. Simulation results showed that DA-SVM achieves competitive performance compared to PSO-SVM and GA-SVM algorithms. DA-SVM is able to find optimal values of SVM parameters.

Elhariri et al. [78] applied two optimization techniques, namely DA and GWO, combined with SVM classification algorithm for solving the electromyography (EMG) signal classification problem. Simulation results showed that GWO-SVM outperformed the DA-SVM approach and the typical SVM classifier with an accuracy of 93.22%.

Feng et al. [79] proposed a combined approach (DA-SVM) based on the hybridization of DA with SVM for predicting the short-term load forecasting of an offshore oil field micro-grids in the Bohai Sea of China. Experimental results demonstrated that DA-SVM has better global search ability and higher prediction accuracy compared to GA-SVM, PSO-SVM, and BPNN models.

Li et al. [80] proposed a hybrid method (IDA-SVM) based on the combination of IDA with SVM for short-term wind power forecasting. The performance of IDA-SVM was tested using real datasets derived from la Haute Borne wind farm in France. Simulation results showed that IDA-SVM gives better performance compared to GA-SVM, DA-SVM, Grid-SVM, back-propagation neural network (BPNN), and Gaussian process regression (GPR) models.

Li et al. [81] proposed a hybrid method (DA-HKRVM) based on the combination of DA with kernel relevant vector machine (KRVM) to predict the tourist flow in different periods and different regions of the scenic spot.

Simulation results demonstrated that DA-HKRVM is a guidance for the efficient development of tourism economy.

3.1.8 Dragonfly algorithm with support vector regression

Li et al. [82] proposed a hybrid method, named ADA-SVR, based on the combination of adaptive DA with a support vector regression (SVR) model for an accurate prediction of porosity. The performance of ADA-SVR was evaluated based on the log data of geophysical conventional logging through neural network modeling and compared with conventional algorithms such as DA-SVR, BP, and ELM algorithms. Experimental results showed the feasibility and performance of ADA-SVR compared to conventional existing methods.

Amroune et al. [57] proposed another hybrid approach (DFS-SVR) based on the combination of DA with SVR for online voltage stability assessment. DFS-SVR was compared to the adaptive neuro-fuzzy inference system (ANFIS) using the IEEE 30-bus and the Algerian 59-bus systems. Experimental results demonstrated that DFS-SVR provides better performance compared to ANFIS.

3.1.9 Dragonfly algorithm with neural network

Yasen et al. [83] proposed an approach based on the hybridization of DA with artificial neural network (ANN), called ANN-DA, for medical prediction. Five real medical datasets were used to train and test its performance. Experimental results demonstrated the efficiency of ANN-DA compared to ANN-ABC and other well-known classifiers.

VeeraManickam et al. [84] proposed a method, named CDF-NN. It is based on the hybridization of the cumulative DA with neural network (NN) for predicting optimally the performance of the students. CDF-NN was compared with other existing algorithms such as back-prorogation algorithm and dragonfly NN, taking into account the MSE and RMSE metrics. Simulation results revealed the performance of CDF-NN compared to other algorithms in the literature. It obtained the values of 16.944 and 4.665 for the MSE and RMSE, respectively.

Chatra et al. [85] developed a hybrid approach called BDADNN. It is based on the hybridization of binary DA with deep neural network using a fitness function for texture image classification. The performance of BDADNN was verified using the two datasets: textured surfaces and KTH-TIPS. Simulation results demonstrated the superior performance of BDADNN compared to SVM in terms of accuracy, sensitivity, and specificity.

Nair and Linda [86] proposed a combined technique (MDA-RNN) based on the hybridization of modified DA with recurrent neural network (RNN) for an efficient maximum power point tracking in hybrid solar and wind energy system. The performance of MDA-RNN was evaluated under variation of irradiance, wind speed change, and variation of load. Simulation results showed the effectiveness of MDA-RNN compared to ACO, BA, and MDA.

3.1.10 Multi-objective dragonfly algorithm

Li et al. [87] proposed a multi-objective DA based on reference point decomposition (RMODA) to solve the wind–solar–hydropower optimal scheduling. The effectiveness of the proposed algorithm was tested taking as example the large-scale hydropower station in Southwest China and compared with NSGAIII. Simulation results showed the superiority of RMODA compared to NSGAIII in terms of convergence and distribution of the solutions.

Khalilpourazari and Khalilpourazary [88] proposed an efficient meta-heuristic algorithm, named multi-objective dragonfly algorithm (MODA). MODA aims to solve a real-work grinding optimization problem and provide efficient Pareto optimal solutions. The authors also implemented a constraint handling (static penalty) technique to handle complex operational constraints of the problem. Simulation results revealed the capability of MODA to find non-dominated Pareto optimal solutions and to give efficient enhancement compared to NSGAII.

Vikram et al. [89] used multi-objective DA for evaluating the performance of process parameters in turn–mill operations. The performance of MODA was evaluated considering three process parameters: tool speed, feed rate, and depth of cut. Simulation results showed the performance of MODA compared to grey relational analysis (GRA) algorithm.

Weijia et al. [90] proposed an improved multi-objective dragonfly algorithm (DMODA) for annual power cut plan arrangement. The external archiving maintenance strategy and the niche sharing mechanism under crowed distance were added to enhance the performance of MODA. Simulation results showed the performance of DMODA compared to the original MODA and MOPSO in terms of convergence speed.

3.1.11 Dragonfly algorithm with extreme learning machine

Salam et al. [91] developed a new hybrid approach, called DA-ELM, based on the hybridization of extreme learning machine (ELM) with DA to solve the prediction problem. DA was exploited to obtain optimal input weights and hidden layer biases. The authors tested the performance of DA-ELM based on ten regression datasets taken from the

UCI repository; they found that DA-ELM outperformed both GA-ELM and PSO-ELM algorithms.

Wu et al. [92] proposed a novel ship classification model, called BDA-KELM, based on the combination of the binary DA with kernel extreme learning machine (KELM) for high-resolution synthetic-aperture radar (SAR) images. The performance of BDA-KELM was evaluated based on six high-resolution TerraSAR-X SAR imagery in comparison with Bayes, k-nearest neighbor (kNN), back-propagation neural network (BPNN), and support vector machine (SVM). Simulation results showed that BDA-KELM achieves better classification performance compared with other existing models; it achieved the classification accuracy of 97%.

3.1.12 Other enhanced dragonfly algorithms

Sudabattula et al. [93] proposed a method based on DA and loss sensitivity factor to solve the renewable distributed generators and capacitors allocation problem. The method was tested on a large-scale 119-bus system and compared with simulated annealing (SA). Simulation results showed the ability of the method to solve the problem compared to SA.

Kumar et al. [94] proposed a method called fractional dragonfly load balancing algorithm (FDLA) to solve the load balancing problem in cluster–cloud computing environments. FDLA was designed by hybridizing fractional calculus (FC) theory with DA and evaluated based on the load values and number of tasks allocated. Experimental results showed the effectiveness of FDLA compared to other existing methods such as PSO, HBB-LB, and standard DA. FDLA attains a minimum load of 0.2133 with the number of tasks allocated as 14.

Acı and Gulcan [95] proposed a modified dragonfly algorithm based on Brownian motion for single- and multi-objective problems. The randomization stage of DA was enhanced using the Brownian motion. The modified DA was evaluated in the optimization of 15 single-objective and six multi-objective problems and compared with the original DA. Numerical results showed that DBG achieves highly competitive results compared to the standard DA.

Suresh et al. [96] proposed an enhanced dragonfly algorithm (ADFA) for solving static and dynamic economic dispatch problems (EDP) considering renewable energy resources and demand response. Static economic dispatch using DFA was carried out on 6-, 17-, and 40-thermal generator test systems. Further, dynamic economic dispatch was carried out on 6- and 17-thermal generator test systems. Simulation results showed that ADFA obtained better results compared to other algorithms existing in the literature.

Sugave et al. [97] proposed an optimization algorithm, named diversity dragonfly algorithm (DDF), for determining the optimal test suites with minimum execution times. The performance of DDF was carried out using five subject programs and compared with TBAT algorithm, systolic genetic search algorithm, and greedy irreplaceability algorithm. Simulation results showed that DDF possesses a higher degree of reduction capacity and gives a lower variance value compared to other existing methods.

Mafarja et al. [98] employed BDA with K-nearest neighborhood (KNN) for solving the feature selection problem. The performance of BDA was evaluated based on nine large-scale medical datasets with a low number of samples, in comparison with BGA, BPSO, BGSA, BBA, and BGWO. Simulation results showed the superiority of BDA compared to other well-known wrapper feature selection methods.

Shelke and Prasad [99] proposed a combined approach, called dragonfly Bayes fusion system (DBFS), based on incorporating DA with Naive Bayes (NB) classifier for detecting the tampered JPEG image for forensic analysis. The performance of DBFS was realized based on 100 uncompressed TIFF images taken from the UCID database in comparison with rule-based classification, fuzzy theory-based classification, average method, and weighted average method. Experimental results showed that DBFS outperformed other existing approaches by obtaining minimum FPR of 0.0490, maximum TPR of 0.8720, and maximum accuracy of 0.9519.

Patil and Atique [100] proposed an adaptive autoregressive model (AA-CDNB) by the integration of the CAVIAR dragonfly algorithm and the Naive Bayes model for identifying the reasons behind tweets provided by various users. The performance of AA-CDNB was evaluated based on the standard BITS PILANI dataset which contains tweets from the online users. Simulation results revealed that AA-CDNB outclassed other models such as NBDF, NB, CDNB, and SentiWordNet algorithms with the values of 1, 0.888, and 0.920 for the sensitivity, specificity, and accuracy metrics, respectively.

Yuan et al. [101] proposed a hybrid method (CFSSDA) based on the combination of DA with Coulomb force search strategy (CFSS) for solving structural optimization problems with stress constraints. The effectiveness of CFSSDA was tested based on three widely used benchmark numerical examples in comparison with DA, BDA, and elite opposition-based DA (EOEDA). Numerical results showed that CFSSDA achieves a significant enhanced convergence rate and a higher accuracy compared to other well-known optimization methods.

Murugaperumal et al. [102] proposed a combined method (ANFMDA) based on the combination of ANFIS with modified DA for optimal energy management of micro-grid-connected system with low cost. Experimental results demonstrated the effectiveness of ANFMDA compared to ABC, DA, and HOMER techniques.

3.2 Hybridized versions of dragonfly algorithm

Many hybrid optimization algorithms based on the hybridization of DA with other optimization meta-heuristic algorithms have been proposed in order to enhance the performance, efficiency, and robustness of the classical DA. Table 4 presents the well-known hybrid DA algorithms in the literature. The details of these hybrid algorithms are given below.

3.2.1 Hybridization with genetic algorithm

Veeramsetty et al. [103] proposed a hybrid genetic dragonfly algorithm (HGDA) based on optimal power flow (OPF) to compute the locational marginal price (LMP) at distributed generation (DG) buses for improving the reliability in radial distribution systems (RDS). HGDA has been implemented on 38-bus RDS and Pacific Gas and Electric Company (PG&E) and 69-bus RDS. Simulation results showed that HGDA enables the distribution company (DISCO) to vastly improve the reliability of the network.

Guo et al. [104] proposed a novel adaptive engine calibration optimization algorithm based on the combination of multi-objective DA, multi-objective GA, fuzzy-based inference system, and sub-structured artificial neural network (SSANN) for controlling the engine parameters. The performance of the proposed model was evaluated based on 15 working points based on different engine speeds. Simulation results revealed that the proposed model improves engine performance and reduces greenhouse emissions.

3.2.2 Hybridization with simulated annealing

Han et al. [105] proposed a hybrid method (IDA) based on the hybridization of DA with SA for solving the limited-buffer flexible flow-shop scheduling problem (LBFFSP). The effectiveness of IDA was tested using four sets of small-scale and four sets of large-scale FFSP standard examples. Experimental results showed that IDA gives a better solution for LBFFSP compared to the original DA and PSO algorithms.

3.2.3 Hybridization with quantum evolutionary algorithm

Mahseur et al. [106] proposed a combined approach based on the combination of DA with quantum evolutionary algorithm (QEA) to solve the quality-of-service multicast routing problem (QoSMRP). In the proposed approach, the equation of DA was used to calculate $\Delta\theta$ in QEA and a quantum representation of the solution by a vector of continuous real values was adopted to avoid discretization of DA. Experimental results showed the scalability of the proposed approach compared to other existing algorithms such as GA, QEA, and DA.

Table 4 Hybridization versions of DA

Hybridization version	Research works
Hybridization with genetic algorithm	Veeramsetty et al. [103] , Guo et al. [104]
Hybridization with simulated annealing	Han et al. [105]
Hybridization with quantum evolutionary algorithm	Mahseur et al. [106]
Hybridization with differential evolution	Xu et al. [107], Duan et al. [108]
Hybridization with ant colony algorithm	Jadhav and Joshi [109]
Hybridization with particle swarm optimization algorithm	Ranjini and Murugan [110], Trivedi et al. [111], Tawhid and Dsouza [113], Shilaja and Ravi [112], Bharanidharan and Rajaguru [114]
Hybridization with crow search algorithm	More and Ingle [115], Kumar and Vimala [116]
Hybridization with bat algorithm	Sureshkumar and Ponnusamy [117], Gonal and Sheshadri [118]
Hybridization with grey wolf optimizer	Shilaja and Arunprasath [119]
Hybridization with ABC algorithm	Ghanem and Jantan [121]
Hybridization with glowworm swarm optimization algorithm	Vinodhini and Gomathy [122]
Hybridization with other algorithms	Xu and Yan [123], Khadanga et al. [124], Ramadhani et al. [126], Elhoseny and Shankar [127]

3.2.4 Hybridization with differential evolution

Xu et al. [107] proposed a method known as improved DA (IDA) based on the hybridization of DA and DE for multilevel color image segmentation. The performance of IDA was tested based on eight color images taken from the Berkeley database and compared with five other existing algorithms such as standard DA, SCA, HSO, BA, and PSO. Simulation results revealed that IDA outperformed these algorithms in terms of standard deviation, structural similarity index, feature similarity index, peak signal-to-noise ratio, and average fitness values.

Duan et al. [108] proposed a hybrid method based on the combination of DA with DE for global optimization problems. The hybrid method combined the exploitation capability of DE and exploration capability of DA to achieve optimal solution. The performance of DA-DE was evaluated using 30 classical benchmark functions in comparison with 16 optimization algorithms. Simulation results demonstrated the effectiveness of DA-DE compared to other existing optimization techniques.

3.2.5 Hybridization with ant colony algorithm

Jadhav and Joshi [109] proposed a hybrid approach (ACADF) based on the hybridization of ACO with adaptive DA for an effective model transformation. The effectiveness of ACADF was evaluated using two measure factors: automatic correctness (AC) and related fitness function. Experimental results showed that ACADF provides better performance for the model transformation compared to other meta-heuristics such as original DA, ADA, and PSO.

3.2.6 Hybridization with particle swarm optimization algorithm

Ranjini and Murugan [110] proposed a memory-based hybrid dragonfly algorithm (MHDA) for solving numerical optimization problems. MHDA combined the exploration capability of DA and exploitation capability of PSO to give optimal solutions. The performance of MHDA was evaluated based on two benchmark functions: basic unconstrained benchmark functions and CEC 2014 test functions. Simulation results demonstrated the efficiency of MHDA compared with some state-of-the-art algorithms.

Trivedi et al. [111] proposed a hybrid approach based on the combination of DA with PSO for global numerical optimization. The hybrid approach used PSO for the exploitation phase and DA for the exploration phase. Simulation results validated the effectiveness of PSO-DA compared to standard DA and PSO.

Shilaja and Ravi [112] proposed a hybrid optimization method based on the hybridization of DA with aging particle swarm optimization (APSO) for handling the optimal power flow (OPF) problem in renewable energy resources. The performance of this hybrid method was tested based on IEEE 30-bus test systems in comparison with improved GA and PSO. Simulation results yielded better results compared to other existing optimization methods.

Tawhid and Dsouza [113] proposed a hybrid method called hybrid binary dragonfly enhanced particle swarm optimization algorithm (HBDESPO) for solving the feature selection. The performance of HBDESPO was evaluated based on 20 standard datasets taking from the UCI repository, and results proved the ability of HBDESPO to give high classification accuracy compared to BDA and EPSO.

Bharanidharan and Rajaguru [114] proposed a method based on the hybridization of DA with SI algorithms such as PSO, ACO, and ABC algorithms for dementia classification. The effectiveness of the method was evaluated based on 65 non-dementia and 52 dementia subjects taken from the OASIS database. Simulation results showed the better effectiveness of the hybrid method in comparison with classical SI algorithms. Hybrid DA-PSO method gives the highest accuracy of 87.18%.

3.2.7 Hybridization with crow search algorithm

More and Ingle [115] proposed a hybrid optimization algorithm, called D-Crow, based on the integration of CSA into DA for getting optimal energy-aware virtual machine migration (VMM). D-Crow was evaluated based on three metrics such as energy consumption, migration cost, and load. Simulation results showed that D-Crow outperformed the basic DA and other existing algorithms such as ACO, modified exponential gravitational search algorithm(MEGSA-VMM), and LR by achieving the minimum values of 11.0639%, 7.3719%, and 10.0368% for the migration cost, load, and energy consumption, respectively.

Kumar and Vimala [116] proposed a hybrid method (C-FDLA) based on the hybridization of the crow search algorithm with integrated fractional dragonfly algorithm for load balancing in cloud computing environments. The authors introduced also the multi-objective model based on the frequency scaling parameters integrated machine capacity, selection probabilities, and data length of the task. C-FDLA was analyzed based on the load values and the number of reallocated tasks. Simulation results proved the effectiveness of C-FDLA compared to other algorithms such as classical DA, FDLA, PSO, and ABC algorithms. C-FDLA gives minimum load value of 0.0913 and the number of tasks reallocated as 11.

3.2.8 Hybridization with bat algorithm

Sureshkumar and Ponnusamy [117] proposed an efficient hybrid approach (MDABSA) based on the hybridization of modified DA with bat search algorithm (BSA) for the power flow management of hybrid renewable energy source in the micro-grid system. The effectiveness of MDABSA was tested in balanced and unbalanced supply of the system during any load changes in comparison with MEHOTSA, GA, PSO, and PI controller. Simulation results showed the effectiveness of MDABSA to manage the power flow compared to other existing algorithms.

Gonal and Sheshadri [118] proposed a hybrid method (HBDFA) based on the combination of DA with BA to provide optimal power flow control in a grid-connected wind–solar system. Experimental results demonstrated that HBDFA gives better performance compared to other existing optimization approaches.

3.2.9 Hybridization with grey wolf optimizer

Shilaja and Arunprasath [119] proposed a hybrid approach based on the hybridization of DA with enhanced grey wolf optimization (GWO) algorithm for solving the optimal load power flow issue. The performance of this approach was evaluated based on IEEE 30-bus system, and results proved that the hybrid approach is more efficient in terms of cost reduction and power loss minimization compared to other existing optimization algorithms.

3.2.10 Hybridization with whale optimization algorithm

Jadhav and Joshi [120] proposed a combined method based on the combination of adaptive DA with WOA for transforming class diagrams to relational schema. The performance of WOADF was evaluated using automatic correctness (AC) and fitness values, and results showed the robustness and effectiveness of WOADF compared to other optimization methods existing in the literature. WOADF gives maximum AC value of 0.812 and fitness value of 0.897, respectively.

3.2.11 Hybridization with ABC algorithm

Ghanem and Jantan [121] proposed a hybrid approach (HAD) based on the combination of ABC algorithm with DA for training multilayer perceptrons (MLPs). HAD was evaluated based on six standard classification datasets taken from the UCI machine learning repository in comparison with nineteen other meta-heuristic algorithms. Simulation results showed that HAD outperformed the other algorithms in terms of greater classification accuracy and smaller mean squared error (MSE).

3.2.12 Hybridization with glowworm swarm optimization algorithm

Vinodhini and Gomathy [122] proposed a hybrid approach, called DA-GSO, based on the hybridization of DA with glowworm swarm optimization (GSO) algorithm for energy-efficient routing in wireless sensor network (WSN). Simulation results showed the superiority of DA-GSO compared to PSO-PSO and PSO-GSO. It improves the lifetime of the network and reduces the network energy consumption.

3.2.13 Hybridization with other algorithms

Xu and Yan [123] proposed a hybrid method (INMDA) based on the hybridization of DA and improved Nelder–Mead simplex algorithm for training multilayer perceptrons (MLPs). INMDA was tested on several well-known benchmark functions with low and large dimensions. Additionally, it was applied for training MLP through three classical classification problems. Simulation results revealed the effectiveness of INMDA to find optimal weight and biases for MLPs compared to other algorithms such as GWO, PSO, GA, ES, and PBIL.

Khadanga et al. [124] proposed a method based on the hybridization of DA with pattern search algorithm (hDF-PS) for studying a tilt integral derivative (TID) controller in an island micro-grid (MG) for frequency control. The robustness of hDF-PS was assessed by considering different disturbances and parametric variations in comparison with GA, PSO, and DA. Simulation results showed that hDF-PS gives superior results compared to conventional algorithms existing in the literature.

Ranjini [125] proposed a memory-based hybrid DA (MHDA) for training multilayer perceptron (MLP). The effectiveness of MHDA was evaluated using five classification datasets and three approximation functions in comparison with GA, ACO, PSO, ES, back-propagation (BP), and DA. Simulation results demonstrated the performance of MHDA to provide optimum set of weight and biases at a higher convergence rate compared to other existing training optimization algorithms.

Ramadhani et al. [126] proposed a nonlinear optimization method called memory-based DA (MHDA) for solving the vertical electrical sounding (VES) data inversion problem. The performance of MHDA was tested using the noise-contaminated synthetic VES data. Experimental results showed the efficiency of MHDA compared to the original DA. MHDA is proved to be an innovative method for solving VES data inversion problem.

Elhoseny and Shankar [127] proposed a combined method (K-Medoid+EDA) based on the hybridization of enhanced DA with K-Medoid clustering model for energy-efficient optimal routing in vehicular ad hoc network (VANET). The performance of K-Medoid+EDA was tested by examining four network parameters: throughput, packet delivery ratio, energy consumption, and network lifetime. Simulation results showed that K-Medoid+EDA gives minimum energy consumption and minimum execution times when compared with existing algorithms.

4 Applications of dragonfly algorithm

DA has been applied to solve a large variety of optimization problems in several fields and areas of research categorized into combinatorial, constrained, and continuous optimization. Some of the applications of DA are summarized in Table 5. The details are given in the following sections.

4.1 Combinatorial optimization

4.1.1 Feature selection

Mafarja et al. [128] proposed a wrapper feature selection method based on BDA and KNN with two objective functions: minimizing the number of selected features and maximizing the classification accuracy. The authors compared their approach with GA and PSO algorithms based on 18 benchmark datasets taken from the UCI data repository. Experimental results showed the superiority of the approach compared to GA and PSO algorithms.

Hariharan et al. [61] proposed an improved binary dragonfly optimization algorithm (IBDFO) based on feature selection for infant cry signals classification. The authors proposed also a feature set using wavelet packet-based nonlinear features. The performance of IBDFO was tested with its basic BDFO algorithm and PSO algorithm. Simulation results showed that IBDFO yields a very promising classification accuracy compared to other existing works algorithms.

4.1.2 Optimal power flow

Bashishtha and Srivastava [129] used DA to solve the optimal power flow (OPF) problem in power systems. The performance of DA was realized based on IEEE 30-bus test systems in comparison with GA, DE, ABC, PSO, and teaching–learning-based optimization (TLBO) algorithms. Numerical results revealed the superiority and effectiveness of DA compared to other approaches available in the literature.

4.1.3 Travel salesman

Hammouri et al. [130] used DA for solving the traveling salesman problem (TSP). The efficiency of DA was assessed based on ten well-known datasets (TSPLIB) with various sizes and complexity levels in comparison with GA, PSO, ACO, and BH. Experimental results showed the superiority of the DA compared to other optimization algorithms available in the literature.

4.1.4 Resource allocation

Amini et al. [131] applied DA for establishing proper resource allocation and providing load balance in cloud computing. The performance of DA was evaluated taking into account the execution time, response time, tasks migration, and load balance. Experimental results proved that DA provided considerable improvements in load balancing, resource allocation, and task scheduling when compared to other methods such as ACO and ACO-PSO.

4.1.5 PID control

Guha et al. [132] employed DA to optimize the controller parameters of the 3-degree-of-freedom (3DOF) proportional–integral–derivate (PID) for the hybrid energy distributed power system (HEDPS). The effectiveness of DA was evaluated in comparison with PSO, DE, BBO, TLBO, krill herd algorithm, and GWO. Computational results revealed better performances of DA compared with the aforementioned algorithms in terms of convergence rate, minimum fitness value, and dynamic performance of the system.

Simhadri et al. [133] used DA to tune the controller parameters of the 2-degree-of-freedom PID (2DOF-PID) for multi-area power system. The performance of DA was evaluated in terms of tie-line power of control areas in power system and settling time of the deviations in frequency. Simulation results showed the superiority of DA compared to other existing optimization methods.

Mishra and Mohanty [134] applied DA to provide optimal parameters of the fractional order PID controller. Optimized FOPID obtained using DA was employed to control the step-back of pressurized heavy water reactor. Simulation results showed that DA-INFOPID outperforms the conventional INFOPID. It reduces the steady-state error and the system settling time.

4.1.6 Vehicle routing problem

Liu et al. [135] used DA for solving the vehicle routing problem with time windows constraints (VRPTW). The effectiveness of DA was tested based on three cost factors:

Table 5 Applications of DA

Category	Problem	Research works
Combinatorial optimization	Feature selection	Mafarja et al. [128], Hariharan et al. [61]
	Optimal power flow	Bashishtha and Srivastava [129]
	Travel salesman	Hammouri et al. [130]
	Resource allocation	Amini et al. [131]
	PID control	Guha et al. [132], Simhadri, et al. [133], Mishra and Mohanty [134]
	Vehicle routing problem	Liu et al. [135]
Constrained optimization	Economic dispatch problem	Pathania et al. [136], Das et al. [137], Suresh and Sreejith [138] Bhesdadiya et al. [139], Palappan and Thangavelu [140]
	Distributed generator	Suresh and Belwin [141], Arulraj and Kumarappan [142]
	Optimal VAR reactive power compensation	Vanishree and Ramesh [143]
	Access point deployment	Debnath et al. [144]
	Stress concentration factor	Jafari et al. [59]
	Global maximum power point tracking	Raman et al. [145]
Continuous optimization	Trainer artificial neural network	Abdulameer [146]
	Concentric circular antenna array	Babayigit [58]
	Optimal harmonic passive filter	Ismael et al. [147]
	Wireless node localization	Daely and Shin [148]
	Image segmentation	Díaz Cortés et al. [149]
	Optimal IIR filter design	Singh et al [150]
	Thermal parameters estimation	Mallick et al. [151]
	RFID network	Hema et al. [152]
	Bearing capacity assessment of footings	Moayedi et al. [153]
	Medical images	Hemamalini and Nagarajan [154], Sarvamangala and Kulkarni [155]
	Multilayer perceptrons	Khishe and Safari [156]

freight transportation costs, overtime penalty costs, and warehouse resident costs. Simulation results proved the efficiency and feasibility of DA to solve the VRPTW.

4.2 Constrained optimization

4.2.1 Economic dispatch

Pathania et al. [136] used DA to solve the economic load dispatch problem with value point effect. The performance of DA was tested based on a modified IEEE 30-bus system containing six thermal generating units and one wind farm in comparison with other meta-heuristics such as QPSO, ABC, and SQO-PSO. Simulation results showed the capability of DA to find the global optimum solution and manage the system constraints compared to other algorithms existing in the literature.

Das et al. [137] used DA for solving the probabilistic economic load dispatch (PED) problem taking into account uncertainties of solar and wind energy. The performance of DA was validated using four test systems in comparison with CSA, ALO, oppositional real-coded chemical reaction optimization, BBO, PSO, and GA. Simulation results showed the effectiveness of DA compared to other well-known optimization algorithms in terms of total generation cost and execution time.

Suresh and Sreejith [138] used DA to solve the static economic dispatch problem with the incorporation of solar energy. DA was evaluated using 6-generator, 15-generator, and 17-generator operational South Indian systems. Simulation results revealed that DA gives minimum cost and converges in low running time compared to some other optimization algorithms available in the literature.

Bhesdadiya et al. [139] applied DA to solve the emission constrained economic dispatch (ECED) problem using a price penalty factor method. The performance of DA was evaluated based on IEEE 30-bus system with six operational generators. Simulation results proved the capability of DA for solving the ECED problem with different price penalty factors.

Palappan and Thangavelu [140] employed DA for solving the optimal reactive power dispatch problem in power systems. The effectiveness of DA was tested based on standard IEEE 14-bus and 30-bus systems and compared with IP, PSO, and DEA algorithms. Simulation results showed the superior performance of DA in solving the reactive power dispatch problem compared to other existing popular algorithms.

4.2.2 Distributed generator

Suresh and Belwin [141] employed DA to determine the optimal size of the distributed generation units at different power factors and improve the voltage profile of the system. Experiments were conducted based on typical IEEE 15-, 33-, and 69-bus radial distribution systems. Simulation results revealed that DA gives best results compared to other optimization algorithms existing in the literature.

Arulraj and Kumarappan [142] employed DA for multiple allocation of distribution generation and capacitor in distribution systems. The performance of DA was tested based on the standard 33-bus distributed systems. Results demonstrated the effectiveness of DA compared to other existing optimization techniques.

4.2.3 Optimal VAR reactive power compensation

Vanishree and Ramesh [143] used DA to optimize the cost and the size of the static VAR compensator (SVC) for voltage profile improvement in power transmission systems. The effectiveness of DA was tested based on IEEE 14- and 30-bus systems and compared with other optimization algorithms such as PSO, TLBO, and hybrid PSO (PSO+SA). Simulation results showed the high suitability of DA for optimal location and size of SVC compared to other existing algorithms.

4.2.4 Access point deployment

Debnath et al. [144] applied DA for the deployment of access points (AP) in a disaster geographic location. The performance of DA was tested to determine the optimal solution of AP allocation, considering the coverage and capacity of AP as constraints. Simulation results showed that DA is 98% accurate.

4.2.5 Stress concentration factor

Jafari et al. [59] adopted DA to optimize the parameters of perforated orthotropic infinite plates involved in the stress analysis with the quasi-triangular cutout. DA was used to evaluate the stress distribution based on Lekhnitskii's analytical solution in comparison with GA and PSO algorithms. Numerical results showed the superiority of DA in optimizing perforated orthotropic plates compared with GA and PSO.

4.2.6 Global maximum power point tracking

In the work of Raman et al. [145], DA was applied to track the global maximum power point of photovoltaic systems. Experimental results demonstrated the superiority of DA compared to PSO algorithm in terms of tracking speed and reducing energy loss during the tracking process.

4.3 Continuous optimization

4.3.1 Trainer artificial neural network

Abdulameer [146] used DA as trainer algorithm for artificial neural network. The performance of DA was evaluated based on a real human brain MRI dataset in comparison with GA and PSO algorithms. Simulation results revealed that DA-based ANN outperforms GA and PSO algorithms in terms of sensitivity, specificity, and accuracy evaluation metrics.

4.3.2 Concentric circular antenna array

Babayigit [58] applied DA for solving the concentric circular antenna array (CCAA) design problem in order to provide maximum sidelobes level (MSL) reduction. The performance of DA was evaluated in two different three-ring design cases with and without center element. Simulation results proved that DA provides the highest MLS reduction for all design cases in comparison with other algorithms such as BBO, SOS, OGSA, SQP, CSO, FA, and EP.

4.3.3 Wireless node localization

Daely and Shin [148] employed DA to estimate the localization of unknown wireless nodes deployed randomly in a designed area. The performance of DA was evaluated in two scenarios: localization with varying the noise percentage of distance measurement and localization with varying the number of unknown nodes. Simulation results indicated that DA produces a low error for range-based localization compared to PSO algorithm.

4.3.4 Image segmentation

Díaz Cortés et al. [149] proposed a segmentation method based on DA for thermographic images to divide them into homogeneous regions with clear borders. The two typical segmentation techniques: Otsu's method and Kapur's entropy, were used as objective functions on DA. The method was compared with GA, PSO, krill herd algorithm (KH), and runner-root algorithm (RRA). Simulation results exhibited a well performance of the proposed method to generate clear images with sharp borders.

4.3.5 Optimal IIR filter design

Singh et al. [150] used DA to solve the infinite impulse response (IIR) filter design problem. The goal was to determine the optimal set of the unknown IIR filter parameters. Experimental results demonstrated the efficiency of DA compared to PSO, BA, and cat swarm optimization (CSO) algorithms.

4.3.6 Thermal parameters estimation

Mallick et al. [151] employed DA to estimate the inverse variable thermal parameters in a functionally graded annular fin. The performance of DA was evaluated for dimensional and non-dimensional temperature field. Simulation results showed that DA obtained the desired thermal parameters without compromising the volume of the fin.

4.3.7 RFID network

Hema et al. [152] used DA to develop a centralized energy-efficient cluster-based protocol to extend the radio frequency identification (RFID) network. The proposed protocol used a high-energy node as cluster head to devote less energy while transmitting aggregated data to base stations. Simulation results showed the efficiency of the proposed protocol compared to LEACH protocol.

4.3.8 Bearing capacity assessment of footings

Moayedi et al. [153] applied DA to investigate the bearing capacity of footing in the position of a classification issue. The performance of DA was tested based on three well-known accuracy indices of MAE, AUC, and MSE in comparison with Harris hawks optimization (HHO) and typical MLP methods. Simulation results showed that DA outperformed HHO and typical PLM methods by obtaining minimum AUC of 0.942 and MSE of 0.1171.

4.3.9 Medical images

Hemamalini and Nagarajan [154] applied DA to provide security to the medical images and determine the effective pixels. The performance of DA was evaluated using maximum objective function (ENeGW) that depends on the maximum wavelet energy, maximum gradient energy, minimum edge level, and the minimum neighborhood pixel strength. Numerical results showed the robustness of DA compared to GA, PSO, and random selection (RS). DA obtained a maximum PSNR of 63.0281 dB and a maximum correlation coefficient at a rate of 0.9830.

Sarvamangala and Kulkarni [155] used DA for solving the medical image registration problem. Simulation results showed that DA gives higher quality image registration compared to ABC and PSO algorithms, but it suffers from longer convergence time.

4.3.10 Multilayer perceptrons

Khishe and Safari [156] used DA for training an MLP NN to classify sonar targets. The effectiveness of DA was evaluated in terms of precision of classification and convergence speed. Experimental results demonstrated the accuracy and efficiency of DA compared to ACO, GSA, BBO, GWO, ALO, and MVO algorithms.

5 Discussion and future works

DA has been used to solve a large variety of different problems. The reasons of its effectiveness and successfulness are mainly the simple inspiration and the use of few control parameters. Similar to other SI, DA has some restrictions and weaknesses. The strength and weaknesses of DA are summarized in Table 6. The main restriction is that the no free lunch (NFL) theorem confirms that an optimization algorithm cannot solve all optimization problems. Moreover, DA may stuck in local optima due to the poor tuning of its control parameters. To overcome that, researchers have proposed a variant of DA as summarized in Tables 3 and 4.

However, there are still a lot of possibilities that can be suggested as future works such as:

- Hybridization of DA with other evolutionary algorithms and meta-heuristics like FA, CS, HS, BBO, and ALO algorithms taking advantages of their operators to enhance the balance between the exploration and exploitation.
- Development of adaptive versions of DA to tune their control parameters.
- Development of modified versions of DA to deal with some complex optimization problems.
- Comparison of the performance of DA with other meta-heuristics such as HS, CS, SSA, and SCA algorithms.
- Application of DA to solve other practical problems in computer science fields (Intrusion detection, text summarization, wireless mesh network planning, visual tracking), electrical engineering (photoelectronic detection, renewable energy optimization, annual energy loss), civil engineering (dam scheduling, optimum design of truss structures, soil stability analysis),

Table 6 Strength and weaknesses of DA

Strength	Weaknesses
Easy to understand and implement	Control parameters tuning
Few control parameters	Premature convergence in some complex optimization algorithms
Reasonable convergence time	No theoretical convergence property
Hybridization with other meta-heuristics and methods	
Good solutions	
Appropriate for large variety of problems	

mechanical engineering (parameter calibration, steel making), and real-world applications (timetabling, self-driving cars, water distribution network optimization).

6 Conclusion

DA is a recent and promising nature-inspired algorithm that has drawn increasing attention from researchers since it was introduced in 2016. This paper gives the literature review of this algorithm. The related studies are organized according to its modifications, hybridizations, and applications. However, there are still many research areas that can be suggested as future works. In the area of DA hybridization, new hybrid algorithms based on the hybridization of DA with other evolutionary algorithms and meta-heuristics should be proposed to enhance both exploitation and exploration. In the area of modified DA, additional studies are needed to develop other DA variants. One interesting research area is parameters tuning, which is very important for all meta-heuristics to solve real-world problems. DA-modified versions are needed to tune its parameters so that a large variety of optimization problems can be solved effectively. Another possible area for future research is the application of this algorithm to solve other practical optimization problems.

Compliance with ethical standards

Conflict of interest The authors declare that there is no conflict of interest with any person(s) or organization(s).

References

1. Fister Jr I, Yang X-S, Fister I, Brest J, Fister D (2013) A brief review of nature-inspired algorithms for optimization. arXiv preprint arXiv:1307.4186
2. Holland JH (1992) Genetic algorithms. Sci Am 267(1):66–73
3. Storn R, Price K (1997) Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. J Glob Optim 11(4):341–359
4. Yao X, Liu Y, Lin G (1999) Evolutionary programming made faster. IEEE Trans Evol Comput 3(2):82–102
5. Beyer HG, Schwefel HP (2002) Evolution strategies—a comprehensive introduction. Nat Comput 1(1):3–52
6. Koza JR (1994) Genetic programming as a means for programming computers by natural selection. Stat Comput 4(2):87–112
7. Baluja S (1994) Population-based incremental learning: a method for integrating genetic search based function optimization and competitive learning. Technical report CMU-CS-94-163, Carnegie Mellon University, USA
8. Simon D (2008) Biogeography-based optimization. IEEE Trans Evol Comput 12(6):702–713
9. Ma H, Simon D, Siarry P, Yang Z, Fei M (2017) Biogeography-based optimization: a 10-year review. IEEE Trans Emerg Top Comput Intell 1(5):391–407
10. Kirkpatrick S, Gelatt CD, Vecchi MP (1983) Optimization by simulated annealing. Science 220(4598):671–680
11. Formato RA (2007) Central force optimization: a new metaheuristic with applications in applied electromagnetics. Prog Electromagn Res 77:425–491
12. Formato RA (2008) Central force optimization: a new nature inspired computational framework for multidimensional search and optimization. In: Krasnogor N, Nicosia G, Pavone M, Pelta D (eds) Nature inspired cooperative strategies for optimization. Springer, Berlin, pp 221–238
13. Formato RA (2009) Central force optimization: a new deterministic gradient-like optimization metaheuristic. Opsearch 46(1):25–51
14. Rashedi E, Nezamabadi-Pour H, Saryazdi S (2009) GSA: a gravitational search algorithm. Inf Sci 179(13):2232–2248
15. Siddique N, Adeli H (2016) Gravitational search algorithm and its variants. Int J Pattern Recognit Artif Intell 30(08):1639001
16. Erol OK, Eksin I (2006) A new optimization method: big bang-big crunch. Adv Eng Softw 37(2):106–111
17. Abedinpourshotorban H, Shamsuddin SM, Beheshti Z, Jawawi DN (2016) Electromagnetic field optimization: a physics-inspired metaheuristic optimization algorithm. Swarm Evol Comput 26:8–22
18. Kaveh A, Bakhshpoori T (2016) Water evaporation optimization: a novel physically inspired optimization algorithm. Comput Struct 167:69–85
19. Kashan AH (2015) A new metaheuristic for optimization: optics inspired optimization (OIO). Comput Oper Res 55:99–125
20. Mirjalili S, Mirjalili SM, Hatamlou A (2016) Multi-verse optimizer: a nature-inspired algorithm for global optimization. Neural Comput Appl 27(2):495–513

21. Kaveh A, Dadras A (2017) A novel meta-heuristic optimization algorithm: thermal exchange optimization. Adv Eng Softw 110:69–84
22. Tzanetos A, Dounias G (2017) A new metaheuristic method for optimization: sonar inspired optimization. In: International conference on engineering applications of neural networks. Springer, Cham, pp 417–428
23. Kaveh A, Ghazaan MI (2017) A new metaheuristic algorithm: vibrating particles system. Sci Iran Trans A Civ Eng 24(2):551
24. Irizarry R (2004) LARES: an artificial chemical process approach for optimization. Evol Comput 12(4):435–459
25. Lam AY, Li VO (2009) Chemical-reaction-inspired metaheuristic for optimization. IEEE Trans Evol Comput 14(3):381–399
26. Alatas B (2011) ACROA: artificial chemical reaction optimization algorithm for global optimization. Expert Syst Appl 38(10):13170–13180
27. Abdechiri M, Meybodi MR, Bahrami H (2013) Gases Brownian motion optimization: an algorithm for optimization (GBMO). Appl Soft Comput 13(5):2932–2946
28. Salmani HS, Eshghi K (2017) A metaheuristic algorithm based on chemotherapy science: CSA. J Optim. https://doi.org/10.1155/2017/3082024
29. Fausto F, Reyna-Orta A, Cuevas E, Andrade ÁG, Perez-Cisneros M (2020) From ants to whales: metaheuristics for all tastes. Artif Intell 53:753–810
30. Geem ZW, Kim JH, Loganathan GV (2001) A new heuristic optimization algorithm: harmony search. Simulation 76(2):60–68
31. Atashpaz-Gargari E, Lucas C (2007) Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. In: IEEE congress on evolutionary computation. IEEE, pp 4661–4667
32. Tan Y Zhu Y (2010) Fireworks algorithm for optimization. In: International conference in swarm intelligence. Springer, Berlin, pp 355–364
33. Rao RV, Savsani VJ, Vakharia DP (2011) Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems. Comput Aided Des 43(3):303–315
34. Fadakar E, Ebrahimi M (2016) A new metaheuristic football game inspired algorithm. In: 1st conference on swarm intelligence and evolutionary computation (CSIEC). IEEE, pp 6–11
35. Eberhart R, Kennedy J (1995) A new optimizer using particle swarm theory. In: MHS'95. Proceedings of the sixth international symposium on micro machine and human science. IEEE, pp 39-43
36. Kennedy J (2010) Particle swarm optimization. Encyclopedia of machine learning. Springer, New York, pp 760–766
37. Dorigo M, Di Caro G (1999) Ant colony optimization: a new meta-heuristic. In: Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406). IEEE, pp 1470–1477
38. Dorigo M, Birattari M (2010) Ant colony optimization. Springer, New York, pp 36–39
39. Yang XS, Deb S (2009) Cuckoo search via Lévy flights. In: IEEE world congress on nature and biologically inspired computing (NaBIC). IEEE, pp 210–214
40. Yang XS (2009) Firefly algorithms for multimodal optimization. In: International symposium on stochastic algorithms. Springer, Berlin, pp 169–178
41. Yang XS (2010) Firefly algorithm, stochastic test functions and design optimisation. Int J Bio-Inspir Comput 2:78–84
42. Fister I, Fister I Jr, Yang XS, Brest J (2013) A comprehensive review of firefly algorithms. Swarm Evol Comput 13:34–46
43. Yang XS (2010) A new metaheuristic bat-inspired algorithm. In: Nature inspired cooperative strategies for optimization (NICSO 2010). Springer, Berlin, pp 65–74
44. Yang XS (2013) Bat algorithm: literature review and applications. Int J Bio-Inspir Comput 5(3):141–149
45. Gandomi AH, Alavi AH (2012) Krill herd: a new bioinspired optimization algorithm. Commun Nonlinear Sci Numer Simul 17(12):4831–4845
46. Wang GG, Gandomi AH, Alavi AH, Gong D (2019) A comprehensive review of krill herd algorithm: variants, hybrids and applications. Artif Intell Rev 51(1):119–148
47. Kaveh A, Farhoudi N (2013) A new optimization method: Dolphin echolocation. Adv Eng Softw 59:53–70
48. Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. Adv Eng Softw 69:46–61
49. Faris H, Aljarah I, Al-Betar MA, Mirjalili S (2018) Grey wolf optimizer: a review of recent variants and applications. Neural Comput Appl 30(2):413–435
50. Mirjalili S (2015) Moth-flame optimization algorithm: a novel nature-inspired heuristic paradigm. Knowl Based Syst 89:228–249
51. Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67
52. Mirjalili S (2015) The ant lion optimizer. Adv Eng Softw 83:80–98
53. Askarzadeh A (2016) A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm. Comput Struct 169:1–12
54. Mirjalili S, Gandomi AH, Mirjalili SZ, Saremi S, Faris H, Mirjalili SM (2017) Salp swarm algorithm: a bio-inspired optimizer for engineering design problems. Adv Eng Softw 114:163–191
55. Mirjalili S (2016) Dragonfly algorithm: a new metaheuristic optimization technique for solving singleobjective, discrete, and multi-objective problems. Neural Comput Appl 27(4):1053–1073
56. Gharehchopogh FS, Gholizadeh H (2019) A comprehensive survey: whale optimization algorithm and its applications. Swarm Evol Comput 48:1–24
57. Amroune M, Bouktir T, Musirin I (2018) Power system voltage stability assessment using a hybrid approach combining dragonfly optimization algorithm and support vector regression. Arab J Sci Eng 43(6):3023–3036
58. Babayigit B (2018) Synthesis of concentric circular antenna arrays using dragonfly algorithm. Int J Electron 105(5):784–793
59. Jafari M, Chaleshtari MHB (2017) Using dragonfly algorithm for optimization of orthotropic infinite plates with a quasi-triangular cut-out. Eur J Mech A Solids 66:1–14
60. Baiche K, Meraihi Y, Hina MD, Ramdane-Cherif A, Mahseur M (2019) Solving graph coloring problem using an enhanced binary dragonfly algorithm. Int J Swarm Intell Res (IJSIR) 10(3):23–45
61. Hariharan M, Sindhu R, Vijean V, Yazid H, Nadarajaw T, Yaacob S, Polat K (2018) Improved binary dragonfly optimization algorithm and wavelet packet based non-linear features for infant cry classification. Comput Methods Progr Biomed 155:39–51
62. Rahman CM, Rashid TA (2019) Dragonfly algorithm and its applications in applied science survey. Comput Intell Neurosci. https://doi.org/10.1155/2019/9293617
63. Abdel-Basset M, Luo Q, Miao F, Zhou Y (2017) Solving 0–1 knapsack problems by binary dragonfly algorithm. In: International conference on intelligent computing. Springer, Cham, pp 491–502
64. Sawhney R, Jain R (2018) Modified binary dragonfy algorithm for feature selection in human papillomavirus-mediated disease

treatment. In: 2018 IEEE international conference on communication, computing and internet of things (IC3IoT), pp 91–95
65. Mafarja M, Aljarah I, Heidari AA, Faris H, Fournier-Viger P, Li X, Mirjalili S (2018) Binary dragonfly optimization for feature selection using time-varying transfer functions. Knowl Based Syst 161:185–204
66. Abuomar L, Al-Aubidy K (2018) Cooperative search and rescue with swarm of robots using binary dragonfly algoritlnn. In : IEEE 15th international multi-conference on systems, signals an devices (SSD), pp 653–659
67. Sayed GI, Tharwat A, Hassanien AE (2019) Chaotic dragonfly algorithm: an improved metaheuristic algorithm for feature selection. Appl Intell 49(1):188–205
68. Sambandam RK, Jayaraman S (2018) Self-adaptive dragonfly based optimal thresholding for multilevel segmentation of digital images. J King Saud Univers Comput Inf Sci 30(4):449–461
69. Jadhav PP, Joshi SD (2018) ADF: adaptive dragonfly optimization algorithm enabled with the TDD properties for model transformation. Int J Datab Theory Appl 11(4):41–58
70. Apare RS, Gujar SN (2019) Implementing adaptive dragonfly optimization for privacy preservation in IoT. J High Speed Netw 25(4):331–348
71. Kouba NEY, Menaa M, Hasni M, Boudour M (2018) A novel optimal combined fuzzy PID controller employing dragonfly algorithm for solving automatic generation control problem. Electr Power Compon Syst 46(19–20):2054–2070
72. Peng X, Jia H, Lang C (2019) Modified dragonfly algorithm based multilevel thresholding method for color images segmentation. Math Biosci Eng 16(6):6467–6511
73. Song J, Li S (2017) Elite opposition learning and exponential function steps-based dragonfly algorithm for global optimization. In: 2017 IEEE international conference on information and automation (ICIA). IEEE, pp 1178–1183
74. Aadil F, Ahsan W, Rehman ZU, Shah PA, Rho S, Mehmood I (2018) Clustering algorithm for internet of vehicles (IoV) based on dragonfly optimizer (CAVDO). J Supercomput 74(9):4542–4567
75. Bhavani R, Prakash V, Chitra K (2019) An efficient clustering approach for fair semantic web content retrieval via tri-level ontology construction model with hybrid dragonfly algorithm. Int J Bus Intell Data Min 14(1–2):62–88
76. Hema C, Sankar S (2016) Energy efficient cluster based protocol to extend the RFID network lifetime using dragonfly algorithm. In : International conference on IEEE communication and signal processing (ICCSP), pp 0530–0534
77. Tharwat A, Gabel T, Hassanien AE (2017) Parameter optimization of support vector machine using dragonfly algorithm. In: International conference on advanced intelligent systems and informatics. Springer, Cham, pp 309–319
78. Elhariri E, El-Bendary N, Hassanien AE (2016) Bioinspired optimization for feature set dimensionality reduction. In : 3rd international conference on IEEE advances in computational tools for engineering applications (ACTEA), pp 184–189
79. Feng Y, Zhang P, Yang M, Li Q, Zhang A (2019) Short term load forecasting of offshore oil field microgrids based on DA-SVM. Energy Proc 158:2448–2455
80. Li LL, Zhao X, Tseng ML, Tan RR (2020) Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm. J Clean Prod 242:118447. https://doi.org/10.1016/j.jclepro.2019.118447
81. Li D, Deng L, Cai Z (2019) Statistical analysis of tourist flow in tourist spots based on big data platform and DA-HKRVM algorithms. Pers Ubiquitous Comput. https://doi.org/10.1007/s00779-019-01341-x
82. Li Z, Xie Y, Li X, Zhao W (2019) Prediction and application of porosity based on support vector regression model optimized by adaptive dragonfly algorithm. Energy Sour Part A Recov Util Environ Eff. https://doi.org/10.1080/15567036.2019.1634775
83. Yasen M, Al-Madi N, Obeid N (2018) Optimizing neural networks using dragonfly algorithm for medical prediction. In: 2018 8th IEEE international conference on computer science and information technology (CSIT), pp 71–76
84. VeeraManickam MRM, Mohanapriya M, Pandey BK, Akhade S, Kale SA, Patil R, Vigneshwar M (2018) Mapreduce framework based cluster architecture for academic student's performance prediction using cumulative dragonfly based neural network. Cluster Comput 22(1):1259–1275
85. Chatra K, Kuppili V, Edla DR (2019) Texture image classification using deep neural network and binary dragonfly optimization with a novel fitness function. Wirel Pers Commun 108(3):1513–1528
86. Nair SP, Mary Linda M (2019) An efficient maximum power point tracking in hybrid solar and wind energy system: a combined MDA-RNN technique. J Intell Fuzzy Syst 37(4):5495–5514
87. Li J, Lu J, Yao L, Cheng L, Qin H (2019) Wind-Solar-Hydro power optimal scheduling model based on multiobjective dragonfly algorithm. Energy Proc 158:6217–6224
88. Khalilpourazari S, Khalilpourazary S (2018) Optimization of time, cost and surface roughness in grinding process using a robust multi-objective dragonfly algorithm. Neural Comput Appl. https://doi.org/10.1007/s00521-018-3872-8
89. Vikram KA, Ratnam C, Lakshmi VVK, Kumar AS, Ramakanth RT (2018) Application of dragonfly algorithm for optimal performance analysis of process parameters in turn-mill operations—a case study. In: IOP conference series: materials science and engineering 310(1): 012154. IOP Publishing
90. Weijia L, Jiahui X, Dong X, Yifeng W, Yuanwen J, Yang L (2018) Multi-objective optimization method of annual power cut plan based on DMODA algorithm. In: 2018 IEEE China international conference on electricity distribution (CICED). IEEE, pp 393–397
91. Salam MA, Zawbaa HM, Emary E, Ghany KKA, Parv B (2016) A hybrid dragonfly algorithm with extreme learning machine for prediction. In: 2016 IEEE international symposium on innovations in intelligent systems and applications (INISTA). IEEE, pp 1–6
92. Wu J, Zhu Y, Wang Z, Song Z, Liu X, Wang W, Zhou J (2017) A novel ship classification approach for high resolution SAR images based on the BDA-KELM classification model. Int J Remote Sens 38(23):6457–6476
93. Sudabattula SK, Kowsalya M, Velamuri S, Melimi RK (2018) Optimal allocation of renewable distributed generators and capacitors in distribution system using dragonfly algorithm. In: 2018 IEEE international conference on intelligent circuits and systems (ICICS). IEEE, pp 393–396
94. Kumar CA, Vimala R, Britto KA, Devi SS (2019) FDLA: fractional dragonfly based load balancing algorithm in cluster cloud model. Cluster Comput 22(1):1401–1414
95. Acı Çi Gülcan H (2019) A modified dragonfly optimization algorithm for single-and multiobjective problems using brownian motion. Comput Intell Neurosci. https://doi.org/10.1155/2019/6871298
96. Suresh V, Sreejith S, Sudabattula SK, Kamboj VK (2019) Demand response-integrated economic dispatch incorporating renewable energy sources using ameliorated dragonfly algorithm. Electr Eng 101(2):421–442
97. Sugave SR, Patil SH, Reddy BE (2017) DDF: Diversity dragonfly algorithm for cost-aware test suite minimization approach for software testing. In: 2017 international conference on intelligent computing and control systems (ICICCS). IEEE, pp 701–707

98. Mafarja M, Heidari AA, Faris H, Mirjalili S, Aljarah I (2020) Dragonfly algorithm: theory, literature review, and application in feature selection. In: Mirjalili S, Song Dong J, Lewis A (eds) Nature-inspired optimizers. Springer, Cham, pp 47–67
99. Shelke PM, Prasad RS (2019) DBFS: dragonfly Bayes fusion system to detect the tampered jpeg image for forensic analysis. Evol Intell. https://doi.org/10.1007/s12065-019-00243-4
100. Patil HP, Atique M (2018) AA-CDNB: adaptive autoregressive CAVIAR-dragonfly optimization with Naive Bayes for reason identification. Evol Intell 11(1–2):3–17
101. Yuan Y, Lv L, Wang X, Song X (2019) Optimization of a frame structure using the Coulomb force search strategy-based dragonfly algorithm. Eng Optim. https://doi.org/10.1080/0305215X.2019.1618290
102. Murugaperumal K, Raj PADV (2019) Energy storage based MG connected system for optimal management of energy: an ANFMDA technique. Int J Hydrog Energy 44(16):7996–8010
103. Veeramsetty V, Venkaiah C, Kumar DV (2018) Hybrid genetic dragonfly algorithm based optimal power flow for computing LMP at DG buses for reliability improvement. Energy Syst 9(3):709–757
104. Guo S, Dooner M, Wang J, Xu H, Lu, G (2017) Adaptive engine optimisation using NSGA-II and MODA based on a sub-structured artificial neural network. In : 23rd international conference on IEEE automation and computing (ICAC), pp 1–6
105. Han Z, Zhang J, Lin S, Liu C (2020) Research on the improved dragonfly algorithm-based flexible flow-shop scheduling. In Proceedings of the 11th international conference on modelling, identification and control (ICMIC2019). Springer, Singapore, pp 205–214
106. Mahseur M, Boukra A, Meraihi Y (2018) QoS multicast routing based on a quantum chaotic dragonfly algorithm. In: International symposium on modelling and implementation of complex systems. Springer, Cham, pp 47–59
107. Xu L, Jia H, Lang C, Peng X, Sun K (2019) A novel method for multilevel color image segmentation based on dragonfly algorithm and differential evolution. IEEE Access 7:19502–19538
108. Duan M, Yang H, Yang B, Wu X, Liang H (2019) Hybridizing dragonfly algorithm with differential evolution for global optimization. IEICE Trans Inf Syst 102(10):1891–1901
109. Jadhav PP, Joshi SD (2020) ACADF: ant colony unified with adaptive dragonfly algorithm enabled with fitness function for model transformation. In: ICCCE 2019. Springer, Singapore, pp 101–109
110. Ranjini KS, MURUGAN S (2017) Memory based hybrid dragonfly algorithm for numerical optimization problems. Expert Syst Appl 83:63–78
111. Trivedi IN, Jangir P, Kumar A, Jangir N, Bhesdadiya RH, Totlani R (2018) A novel hybrid PSO-DA algorithm for global numerical optimization. In: Perez G, Mishra K, Tiwari S, Trivedi M (eds) Networking communication and data knowledge engineering. Springer, Singapore, pp 287–298
112. Shilaja C, Ravi K (2017) Optimal power flow using hybrid DA-APSO algorithm in renewable energy resources. Energy Proc 117:1085–1092
113. Tawhid MA, Dsouza KB (2018) Hybrid binary dragonfly enhanced particle swarm optimization algorithm for solving feature selection problems. Math Found Comput 1(2):181–200
114. Bharanidharan N, Rajaguru H (2019) Performance enhancement of swarm intelligence techniques in dementia classification using dragonfly-based hybrid algorithms. Int J Imaging Syst Technol. https://doi.org/10.1002/ima.22365
115. More NS, Ingle RB (2018) Energy-aware VM migration using dragonfly-crow optimization and support vector regression model in cloud. Int J Model Simul Sci Comput 9(06):1850050
116. Kumar CA, Vimala R (2018) C-FDLA: crow search with integrated fractional dragonfly algorithm for load balancing in cloud computing environments. J Circuits Syst Comput 28(07):1950115
117. Sureshkumar K, Ponnusamy V (2019) Power flow management in micro grid through renewable energy sources using a hybrid modified dragonfly algorithm with bat search algorithm. Energy 181:1166–1178
118. Gonal V, Sheshadri GS (2019) A hybrid bat-dragonfly algorithm for optimizing power flow control in a grid-connected wind-solar system. Wind Eng. https://doi.org/10.1177/0309524X19882429
119. Shilaja C, Arunprasath T (2019) Internet of medical things-load optimization of power flow based on hybrid enhanced grey wolf optimization and dragonfly algorithm. Future Gener Comput Syst 98:319–330
120. Jadhav PP, Joshi SD (2019) WOADF: whale optimization integrated adaptive dragonfly algorithm enabled with the TDD properties for model transformation. Int J Comput Intell Appl 18(04):1950026
121. Ghanem WA, Jantan A (2018) A cognitively inspired hybridization of artificial bee colony and dragonfly algorithms for training multi-layer perceptrons. Cognit Comput 10(6):1096–1134
122. Vinodhini R, Gomathy C (2019) A hybrid approach for energy efficient routing in WSN: using DA and GSO algorithms. In International conference on inventive computation technologies. Springer, Cham, pp 506–522
123. Xu J, Yan F (2019) Hybrid Nelder–Mead algorithm and dragonfly algorithm for function optimization and the training of a multilayer perceptron. Arab J Sci Eng 44(4):3473–3487
124. Khadanga RK, Padhy S, Panda S, Kumar A (2018) Design and analysis of tilt integral derivative controller for frequency control in an islanded microgrid: a novel hybrid dragonfly and pattern search algorithm approach. Arab J Sci Eng 43(6):3103–3114
125. Ks SR (2019) A study on performance of MHDA in training MLPs. Eng Comput 36(6):1820–1834
126. Ramadhani I, Minarto E (2019) memory based hybrid dragonfly algorithm (MHDA): a new technique for determining model parameter in vertical electrical sounding (VES) data. J Phys Conf Ser 1245(1):012020
127. Elhoseny M, Shankar K (2020) Energy efficient optimal routing for communication in VANETs via clustering model. In: Emerging technologies for connected internet of vehicles and intelligent transportation system networks. Springer, Cham, pp 1–14
128. Mafarja MM, Eleyan D, Jaber I, Hammouri A, Mirjalili S (2017) Binary dragonfly algorithm for feature selection. In: IEEE international conference on new trends in computing sciences (ICTCS). IEEE, pp 12–17
129. Bashishtha TK, Srivastava L (2016) Nature inspired meta-heuristic dragonfly algorithms for solving optimal power flow problem. Nature 5(5):111–120
130. Hammouri AI, Samra ETA, Al-Betar MA, Khalil RM, Alasmer Z, Kanan M (2018) A Dragonfly algorithm for solving traveling salesman problem. In : 8th IEEE international conference on control system, computing and engineering (ICCSCE), pp 136–141
131. Amini Z, Maeen M, Jahangir MR (2017) Providing a balancing method based on dragonfly optimization algorithm for resource allocation in cloud computing. Int J Netw Distrib Comput 6(1):35–42
132. Guha D, Roy PK, Banerjee S (2018) Optimal tuning of 3 degree-of-freedom proportional-integral-derivative controller for hybrid

distributed power system using dragonfly algorithm. Comput Electr Eng 72:137–153
133. Simhadri K, Mohanty B, Rao UM (2019) Optimized 2DOF PID for AGC of multi-area power system using dragonfly algorithm. In: Applications of artificial intelligence techniques in engineering. Springer, Singapore, pp 11–22
134. Mishra S, Mohanty BK (2019) Step-back control of pressurized heavy water reactor by Infopid using DA optimization. In: Applications of artificial intelligence techniques in engineering. Springer, Singapore, pp 497–507
135. Liu C, Tao W, Zhao C, Li X, Su Y, Sun Z (2019) Research on vehicle routing problem with time windows based on the dragonfly algorithm. In: IEEE international conference on dependable, autonomic and secure computing, international conference on pervasive intelligence and computing, international conference on cloud and big data computing, international conference on cyber science and technology congress (DASC/PiCom/CBDCom/CyberSciTech). IEEE, pp 142–148
136. Pathania AK, Mehta S, Rza C (2016) Economic load dispatch of wind thermal integrated system using dragonfly algorithm. In: 2016 7th India international conference on power electronics (IICPE). IEEE, pp 1–6
137. Das D, Bhattacharya A, Ray RN (2019) Dragonfly Algorithm for solving probabilistic economic load dispatch problems. Neural Comput Appl. https://doi.org/10.1007/s00521-019-04268-9
138. Suresh V, Sreejith S (2017) Generation dispatch of combined solar thermal systems using dragonfly algorithm. Computing 99(1):59–80
139. Bhesdadiya RH, Pandya MH, Trivedi IN, Jangir N, Jangir P, Kumar A (2016) Price penalty factors based approach for combined economic emission dispatch problem solution using dragonfly algorithm. In: International conference on IEEE energy efficient technologies for sustainability (ICEETS), pp 436–441
140. Palappan A, Thangavelu J (2018) A new meta heuristic dragonfly optimizaion algorithm for optimal reactive power dispatch problem. Gazi Univers J Sci 31(4):1107–1121
141. Suresh MCV, Belwin EJ (2018) Optimal DG placement for benefit maximization in distribution networks by using dragonfly algorithm. Renew Wind Water Solar 5(1):4
142. Arulraj R, Kumarappan N (2018) Simultaneous multiple DG and capacitor installation using dragonfly algorithm for loss reduction and loadability improvement in distribution system. In : IEEE international conference on power, energy, control and transmission systems (ICPECTS), pp 258–263
143. Vanishree J, Ramesh V (2018) Optimization of size and cost of static var compensator using dragonfly algorithm for voltage profile improvement in power transmission systems. Int J Renew Energy Res (IJRER) 8(1):56–66
144. Debnath S, Jee A, Baishya S, Arif W, Saikia PP, Naafi S (2018) Access point planning for disaster Scenario using dragonfly algorithm. In : 5th international conference on IEEE signal processing and integrated networks (SPIN), pp 226–231
145. Raman G, Raman G, Manickam C, Ganesan SI (2016) Dragonfly algorithm based global maximum power point tracker for photovoltaic systems. In: International conference on swarm intelligence. Springer, Cham, pp 211–219
146. Abdulameer AT (2018) An improvement of MRI brain images classification using dragonfly algorithm as trainer of artificial neural network. Ibn AL-Haitham J Pure Appl Sci 31(1):268–276
147. Ismael S, Abdel Aleem SHE, Abdelaziz A, Bendary F (2019) Optimal harmonic passive filters for power factor correction, harmonic mitigation and electricity bill reduction using dragonfly algorithm. In: 25th International conference on electricity distribution. CIRED, pp 1–5
148. Daely PT, Shin S Y (2016) Range based wireless node localization using dragonfly algorithm. In: Eighth international conference on IEEE ubiquitous and future networks (ICUFN). IEEE, pp 1012–1015
149. Díaz-Cortés MA, Ortega-Sánchez N, Hinojosa S, Oliva D, Cuevas E, Rojas R, Demin A (2018) A multi-level thresholding method for breast thermograms analysis using dragonfly algorithm. Infrared Phys Technol 93:346–361
150. Singh S, Ashok A, Kumar M, Rawat TK (2019) Optimal design of IIR filter using dragonfly algorithm. In: Applications of artificial intelligence techniques in engineering. Springer, Singapore, pp 211–223
151. Mallick A, Ranjan R, Prasad DK (2019) Inverse estimation of variable thermal parameters in a functionally graded annular fin using dragonfly optimization. Inverse Probl Sci Eng 27(7):969–986
152. Hema C, Sankar S (2017) Performance comparison of dragonfly and firefly algorithm in the RFID network to improve the data transmission. J Theor Appl Inf Technol 95(1):59
153. Moayedi H, Abdullahi MAM, Nguyen H, Rashid ASA (2019) Comparison of dragonfly algorithm and Harris Hawks optimization evolutionary data mining techniques for the assessment of bearing capacity of footings over two-layer foundation soils. Eng Comput. https://doi.org/10.1007/s00366-019-00834-w
154. Hemamalini B, Nagarajan V (2018) Wavelet transform and pixel strength-based robust watermarking using dragonflyoptimization. Multimed Tools Appl. https://doi.org/10.1007/s11042-018-6096-0
155. Sarvamangala DR, Kulkarni RV (2019) A comparative study of bio-inspired algorithms for medical image registration. In: Mandal J, Dutta P, Mukhopadhyay S (eds) Advances in intelligent computing. Springer, Singapore, pp 27–44
156. Khishe M, Safari A (2019) Classification of sonar targets using an MLP neural network trained by dragonfly algorithm. Wirel Pers Commun 108(4):2241–2260