A Systematic Review on Bat Algorithm: Theoretical Foundation, Variants, and Applications

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Abstract

Bat algorithm (BA) is a population-based metaheuristic algorithm inspired by echolocation behavior of bat. After the development of BA in 2010, it becomes the attention of researchers from various domains. It has been successfully applied in various real-life engineering problems. This paper presents a comprehensive review of BA. The biological inspiration and working of BA are deliberated. The variants of BA namely improved, hybrid, levy flight, chaotic, binary, and multiobjective are analyzed in detail. The applications of BA in different research domains are investigated. The current challenges and future research directions of BA are discussed. Besides highlighting the new developments in structure of BA, this study can be act as a baseline for young researchers to enhance the performance of their metaheuristic algorithms on adapting the BA. This study will encourage the young researchers and scientists to use BA in their research problems.

1 Introduction

In the last few decade, real-life problems are solved through optimization techniques. The real-life problems are complex in nature and have a large number of constraints. Due to complex nature, classical techniques such as Lagrange's multiplier and integer programming are unable to provide the optimal solutions. The main drawbacks of classical techniques are trapped in local optima and unable to provide a good quality solution [1]. To tackle these problems, metaheuristic algorithms (MHAs) are developed in the recent years. MHAs attain the optimal solutions for complex problems. MHAs have robustness, flexibility, computational efficient, and evade the entrapment of local optima [2, 3]. Due to these features, researchers have got attention towards MHAs.

According to number of solutions generated, MHAs are broadly categorized into two main classes namely single-solution and population-based MHAs (see Fig. 1) [4]. The single-solution MHAs (SSMHAs) generate a candidate solution, which is modified through iterative process. The well-known SSMHAs are tabu search (TS), simulated annealing

(SA), and macro-canonical annealing (MA). The slow convergence rate, sensitive towards the initial control parameters, and limited computing power/resources required are the main features of SSMHAs [5]. Population-based MHAs (PMHAs) generate a set of solutions, which are modified through the improvisation process. Unlike SSMHAs, PMHAs are more focus towards the global exploration [6]. The main features of PMHAs are fast converge rate and more computer power/resources required [7]. Due to these features, PMHAs are widely used in real-life scenario.

PMHAs are further classified into three general categories namely physics-inspired, evolutionary-inspired, and swarm-inspired algorithms. In physics-inspired algorithms, the positions of search agents are modified through the phenomenon and rules of physics. These algorithms use the concepts of electromagnetism, electrostatics, demagnetization, and newton and gravitational rules [8]. The well-known physics-inspired algorithms are gravitational search algorithm (GSA), electromagnetic field optimization (EMPO), and ray optimization (RO). The evolutionary algorithms are inspired from the biological evolution such as mutation, selection, and reproduction [9]. The well-known evolutionary algorithms are genetic algorithm (GA), evolutionary strategy (ES), differential evolution (DE), and genetic programming (GP). The third category is swarm-inspired PMHA.

In swarm-inspired algorithms, the algorithms are designed by studying the behavior of different living insects

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Fig. 1 Classification of metaheuristic algorithms
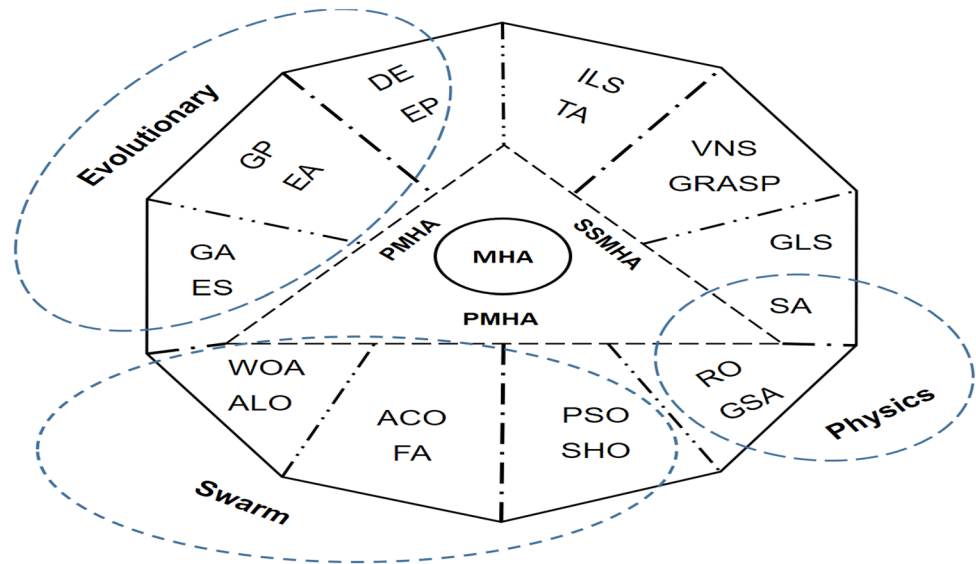
such as ants, bats, fishes, etc. [10]. The self-organization and decentralized control are two special features, which are used by swarm-inspired algorithms. These features are responsible for an emergent behavior. Emergent behavior is a collective property that depends on relationships among one another and cannot be predicted by observing the individual parts. The well-known swarm-inspired algorithms are ant colony optimization (ACO) [11], particle swarm optimization (PSO) [12], firefly algorithm (FA) [13], artificial bee colony (ABC) [14], and harmony search algorithm (HSA) [15]. The main focus of these algorithms is to maintain the balance between exploration and exploitation. The exploration is responsible to explore the whole search space. While, the exploitation is responsible to exploit the most promising area. Recently, many algorithms are developed based on nature of insects, animals, and birds to achieve the balance between these factors.

Yang [26] developed a swarm-inspired metaheuristic algorithm, named as bat algorithm (BA). BA mimics the echolocation behavior of bats. BA is simple, ease to implement, and understandable. Due to the unique feature of echolocation, researchers from different domains are attracted towards BA. BA has been widely used in data mining, mechanical engineering, civil engineering, cloud computing, patter recognition, and medical mining. Hence, there is a need to study the new evolving areas of modifications in the structure of BA and its applications. The following factors are responsible to motivate us for conducting the review on BA.

- BA has been successfully applied in various real-life engineering problems. Henceforth, the authors were motivated to study this algorithms.

- It is observed that review paper provides in-depth knowledge of particular topic and save the time of scientists/researchers to get the insight information of a specific topic.
- The existing review papers did not consider the recent advancement in variants and applications.

This paper covers the various variants and applications of BA, which are not discussed in the existing review papers. The main aim of this paper is to present a systematic review of BA and motivate the young scientists to use BA in their research problems. This paper recapitulates BA in four-ply. These are:

1. Structure of BA that consists of various control parameters of BA.
2. Modifications in the structure of BA that involve improvements and hybridization with the existing metaheuristic algorithms.
3. Applicability of BA that consists of mechanical engineering, cloud computing, medical imaging, networking, and industrial engineering.
4. Future research directions of BA that comprehends the utilization of hyper-heuristics, adaptive mechanism, and multi-population.

The remaining structure of this paper is as follows. Section 2 presents the research methodology used in this study. Section 3 discusses the working of classical bat algorithm. The various modifications in BA are presented in Sect. 4. Section 5 presents the several application domains of BA. The possible research directions are mentioned in Sect. 6. The concluding remarks are drawn in Sect. 7.

2 Research Methodology

This section presents the related studies towards BA followed by the assortment of research articles used in this study.

2.1 Related Studies

Yang and He [16] presented an overview of BA. They identified the variants of BA, applications, and challenges associated with BA. Chawla and Duhan [17] focused on reviewing the applications and variants of BA. However, the future research directions were not discussed in their study. Kongkaew [18] presented the applications of BA in discrete domain. However, the comparative analysis of different applications was done. The variants of BA were not investigated in their study. Zebari et al. [19] discussed the variants and applications of BA. However, the detail investigation of variants and applications was not mentioned.

Gagnon et al. [20] analyzed the performance of BA on well-known test functions. It is found from their study that BA suffers from plateaus. Umar and Rashid [21] focused on reviewing the advancements of BA for different application domains. The provided the comparative analysis of fifteen applications and twenty variants of BA. Kaur and Kumar [22] discussed the mathematical formulation of twenty-eight variants of BA. They focused on nine different applications of BA. The challenges and future research directions were not investigated in their study.

The advancement in BA has been done to resolve the real-life problems. Hence, there is a need to conduct a survey of new research articles that covers the modification in structure of BA and applications of BA. This study covers more than ninety variants of BA and more than hundred applications.

2.2 Review Methodology

The PRISMA [23–25] guidelines are used to conduct the review of bat algorithm (BA). Web of Science, Google Scholar, and PubMed databases have been used for the selecting the research articles related to BA. Beside this, the manual search has also been conducted. The search string such as "Bat algorithm", "((Bat Search) AND (application))", "Improved BA", "((Variant) AND (BA))", "((Hybrid) AND (BA))" and "((Applications) AND (BAT))" were used to search the relevant publications. The advancements in structure of BA were also selected. 19,750 research papers were selected in identification phase. Figure 2 depicts the search string used for collecting the research papers.

During the screening phase, all the unrelated, inappropriate, and duplicate research papers were removed. Thereafter, 684 research papers were left. 213 research papers were eliminated after reading the title, abstract, and introduction. The remaining 471 research papers were investigated through removal criteria and 341 papers were removed. Thereafter, 130 research papers were sent to eligibility phase. In this phase, 100 research papers were excluded after reading full papers. Finally, 30 research papers were selected to conduct the systematic review of BA in included phase of PRISMA. Table 1 presents the criteria for selecting and rejecting the research papers. Figure 3 shows the different phases of PRISMA for this study.

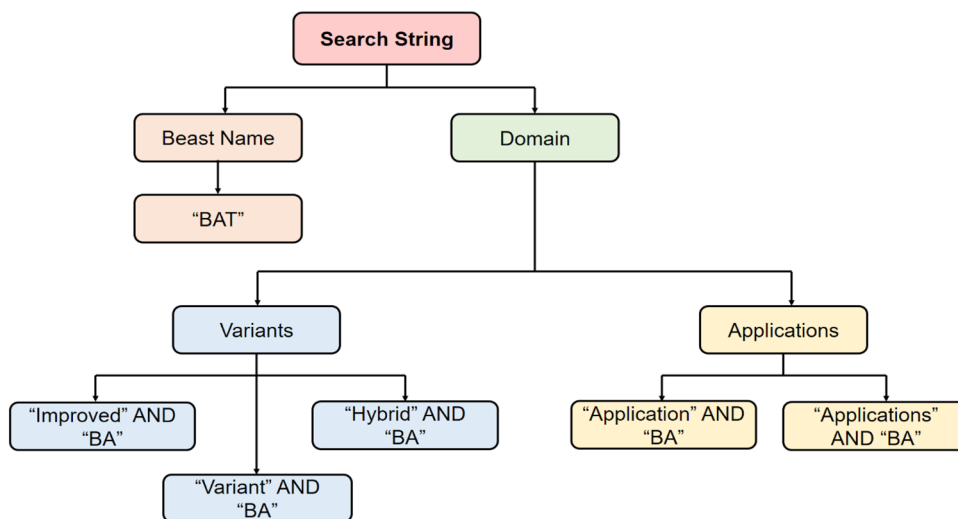**Fig. 2** Search query used for searching the research papers

Table 1 Selection and removal criteria for included papers

S. No	Parameter	Removal criteria	Selection criteria
1	Time duration	Research papers related to BA published before 2010	Research papers related to BA published from 2010–2021
2	Comparison	Research papers addressing the other metaheuristic algorithms	Research papers addressing the BA and its variants
3	Study	Research comprising patent, white papers, technical report, paper in other languages rather than in English	Research comprising theoretical foundation, applications and experimental consequences
4	Application	Research papers on astronomy, finance, and cheminformatics	Research papers having image processing, software, mechanical, civil, industrial, cloud computing, networking, and scheduling
5	Analysis	Research papers having different control parameters of other optimization algorithms	Research papers having various parameters of BA
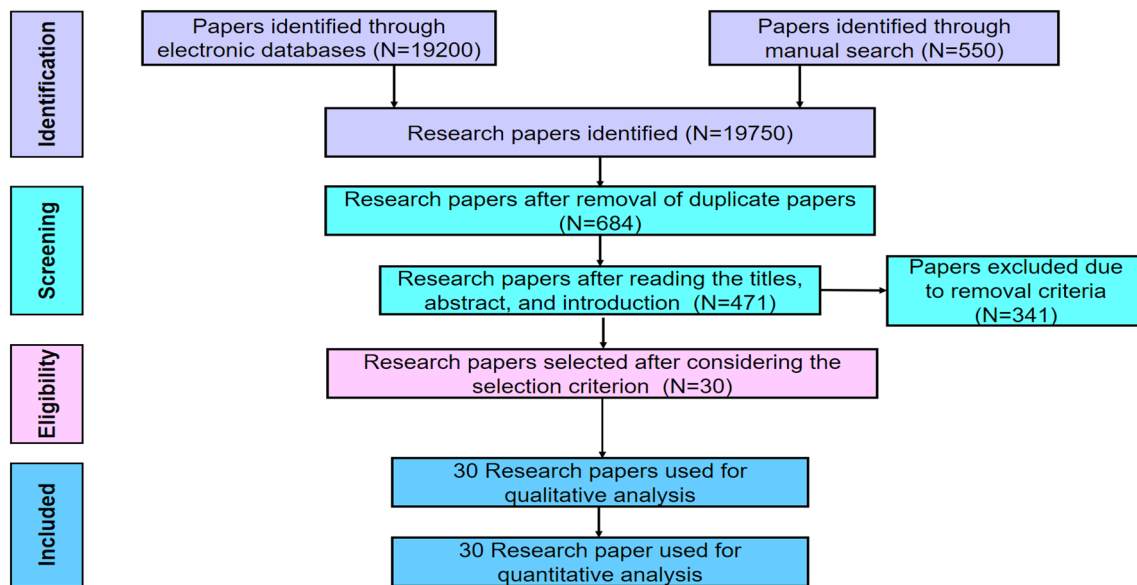
Fig. 3 PRISMA methodology used for selection of research papers

3 Classical Bat Algorithm

This section presents the inspiration behind bat algorithm followed by detail description of classical bat algorithm.

3.1 Inspiration

Bats have an ability to fly in the complete darkness and attack on the prey. The echolocation property of bats help them to do these tasks. They emit a loud pulse and then wait for the echo reflected from the prey [26]. Their pulse frequency and hunting strategies vary with species of bats. Their loudness varies between searching and approaching the prey. For echolocation, short frequency modulated signals are used by most bats, while some other bats use constant-frequency signals. The pulses emitted by bats are lies in the frequency range of 25 kHz to 150 kHz. These pulses can last for 8 to 10 ms [27]. The microbat emits 10 to 20 sounds per second and a maximum of up to 200 sounds per second while searching for prey. The sound produced from microbats is not detected by human ear. However, these can be easily detect through some specific devices [28].

Bats have a distinct acoustic system to differentiate background noise and audible signal. Some bats are very good predators. They usually monitor the surroundings and waiting for their prey. If the signal received without any distribution, then it indicates no prey in this region. Otherwise, prey is present in the specified region and detected through vibration in echolocation frequency.

Algorithm Bat algorithm (BA) is a widely used population-based metaheuristic algorithm that inspired from the echolocation behaviour of microbats with fluctuating pulse rates of

emission and loudness [27]. The echolocation characteristics of microbats play a vital role in the development of BA. The echolocation property is used to navigate in complete darkness and identify the prey. Yang [26] developed a bat algorithm (BA), which is based on the properties of bats. These are [26]:

- With the help of echolocation, the bat can sense the distance of obstacle and differentiate the prey from the obstacle/background.
- Bats fly randomly with velocity z_i at position p_i with a frequency f_{min}, varying wavelength λ and loudness A_0 to search for prey. Depending on the location of their target, the rate of pulse emission and the wavelength of the pulse can vary.
- Loudness varies from A_0 (large positive value) to A_{min} (minimum constant value).

The above-mentioned rules are used to compute the velocity (z_i^t) and position (p_i^t) of bats. The mathematical formulations for z_i^t and p_i^t are given below [26, 29]:

$$f_i = f_{\min} + \left(f_{\max} - f_{\min}\right) \times \beta \tag{1}$$

$$z_i^t = z_i^{t-1} + \left(p_i^t - p_*\right) \times f_i \tag{2}$$

$$p_i^t = p_i^{t-1} + z_i^t \tag{3}$$

where β lies in the range of [0,1]. It is a random vector drawn from a uniform distribution and p_* is the best solution among bats. Randomly, a frequency is assigned to the bat that varies from f_{min} to f_{max}. Loudness (A_i) and rate of pulse emission (R_i) are used to control the mechanism of exploration and exploitation. The rate of emission and loudness decrease when the bat approaches the prey or has captured it. Loudness varies between A_{min} and A_{max}. Here, the value of A_{min} is zero signifies the bat has captured the prey and stopped the emitting sound. Loudness (A_i) can be computed as [26]:

$$A_i^{t+1} = \alpha A_i^t \tag{4}$$

Rate of pulse emission (R_i) can be computed as [26]:

$$R_i^{t+1} = R_i^0 \left[1 - \exp\left(-\gamma t\right)\right] \tag{5}$$

Here, $\alpha \in [0,1]$ and $\gamma > 0$ are constant parameters.

Algorithm 1 depicts the pseudo code of BA [26–29]. The general steps of BA are given below:

Step 1. Initialize the population of bats and control parameters such as p_i, z_i, R_i and A_i.

Step 2. Evaluate the fitness value of individuals and store the best position of bat.

Step 3. Generate new solutions by adjusting the frequency of bats.

Step 4. Update the velocity and position of bats.

Step 5. If a random number is greater than R_i, then select a bat among the current best available bats and perform local search operation around the selected bat.

Step 6. Generate a solution through random fly of bat.

Step 7. If a random number is less than A_i and fitness is greater than best solution, then randomly generated solution is accepted.

Step 8. Update loudness and pulse emission rate.

Step 9. Rank the bats and determine the position of best bat.

Step 10. Repeat Steps 3-9 until termination criteria is not satisfied.

Algorithm 1: Classical Bat Algorithm

Input:

    Bat population size, n

    Maximum number of iterations, MaxItr

Output:

    Global best solution, p_{best}

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begin

    Generate initial population of n bats p_i $(i = 1, 2, ..., n)$

    Initialize the control parameter f_i, R_i, A_i and $t = 0$

    Compute the fitness of each bat

    Identify the best bat based on fitness i.e., p_{best}

   while *$(t < MaxItr)$*

$$f = f_{\min} + \left(f_{\max} - f_{\min}\right) \times \beta$$

$$z^{t+1} = z^t + \left(p^t - p_*\right) \times f$$

$$p_{tm} = p^t + z^{t+1}$$

    for *i=1 to n* ***do***

        if *$Rand > R_i^t$* ***then***

$$p_{tm,i} = p_* + \delta \times Norm(0,1)$$

        end if

        if *$Rand < A_i^t$* ***and*** *$fit\left(p_{tmp,i}\right) < fit\left(p_*\right)$* ***then***

$$p_* = p_{tm,i}$$

$$p^{t+1} = p_{tm}$$

$$R_i^{t+1} = R_0 \left[1 - \exp\left(-\gamma t\right)\right]$$

$$A_i^{t+1} = \alpha A_i^t$$

        end if

     end for

     Increment the current iteration t by 1.

   end while

   return the best solution, p_*

end

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4 Variants of BA

In the recent years, researchers have been attracted towards BA to resolve the real-life problems in various domains. Due to this, researchers tried to modify the structure of BA to enhance its performance. The modifications have been done in three foremost facets. First, the performance of BA is enhanced through modification in control parameters. Second, the components of BA are hybridized with other optimization algorithms. Third, the structure of BA was modified according to problem type and search space. Based on the above-mentioned facets, the variants of BA are classified into six categories namely, improved, hybrid, binary, chaotic, Levy flight-based, and multi-objective BAs (see Fig. 4).
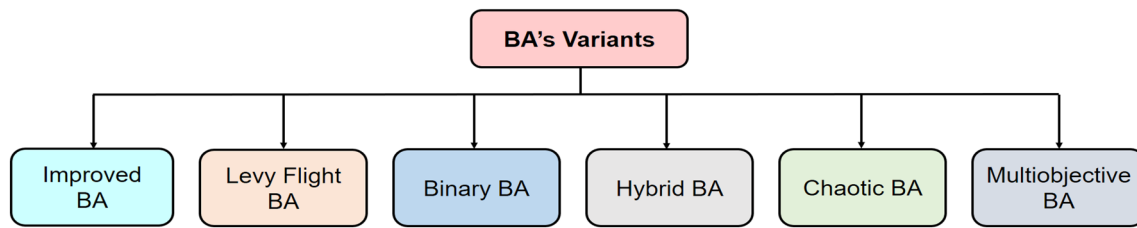
Fig. 4 Variants of BA

4.1 Improved BA

To improve the performance of BA, Jun et al. [30] proposed four modifications in BA. These modifications were performed in movement of bats, pulse rate, loudness, and local search mechanism. The proposed BA was known as directional BA (DBA). DBA was evaluated on benchmark problems and superior to the existing algorithms. Chen et al. [31] proposed a guided BA (GBA) by incorporating the Doppler Effect in BA. The Doppler Effect was responsible for frequency shift of bats. Due to this, bats were able to move towards the recent best bat. The search process were also used to determine the better position nearby the recent best bat. However, GBA did not utilize the self-adaptive strategy for echoes produced by Doppler effect. To resolve this problem, Meng et al. [32] introduced a self-adaptive strategy in new bat algorithm (NBA). The habitat selection was added in NBA. NBA provided better results than GBA. However, it suffers from parameter tuning problem. Wang et al. [33] presented an adaptive BA (ABA) that dynamically adjust the bat's speed and direction. The inertia weight was incorporated in ABA to update the position of bats. On the similar concept of ABA, Wang et al. [34] developed a new algorithm that integrated BA and recollection mechanism and known as RBA. The time varying inertia weight was also added in RBA to update the position of bats.

Li and Zhou [35] devised a complex-value BA (CVBA) that uses the complex-value encoding scheme. The real and imaginary parts were used to encode the variable and updated in parallel fashion. The angles and modules of complex variable was used to design the fitness function. DE strategy was used to enhance the search ability of CVBA. CVBA outperformed the other variants of BA in terms of diversity. Dao et al. [36] presented a compact version of BA (CoBA). In CoBA, the population bat was replaced with probability vector. CoBA performed better than BA in terms of resource usage. To enhance the performance of BA, Ramli et al. [37] proposed modifications in dimension and inertia weight. The modified BA (MBA) was evaluated on ten benchmark test functions. MBA has better exploration rate than BA. Fister et al. [38] introduced a quaternion representation of bats and used in BA. The modified algorithm

was known as quaternion BA (QBA). They used *span* function for mapping quaternion into real representation. QBA was superior to BA for high-dimensional problems. Yilmaz et al. [39] proposed a modified BA (MoBA) that utilizes the update strategies for both pulse rate and loudness. A local search mechanism was also incorporated in MoBA. MoBA provided better performance than BA. However, it was unable to provide optimal solution in high dimensional problems.

Alam and Kabir [40] developed a BA that utilizes the concept of self-adaptive mutation (BA-SM). Gaussian and Cauchy mutation schemes were used in BA-SM. The probability function was used to select one mutation scheme among them. The performance of BA-SM was better than BA. Yilmaz and Kucuksille [41] suggested modifications in BA (IBA) to enhance the performance of BA. The inertia weight factor was used to update the positions of bats. The frequency was also modified. IBA was superior to BA in terms of fitness values. Jamil et al. [42] developed an extended version of BA (ExBA) that utilized the concept of levy flights. The variations in pulse rate and loudness were also done. ExBA was evaluated on 70 test functions and attained superior performance over the existing algorithms. Yilmaz and Kucuksille [43] devised three modifications in BA and known as an enhanced BA (EBA). Inertia weight factor was used to avoid the premature convergence. The modification in velocity was done to control the dispersion of solutions. The concept of IWO was used to improve the exploitation ability of BA. EBA was more efficient than BA. Tsai et al. [44] devised an evolved BA (EvBA). EvBA modified the movements of bats. The sound speed was used to compute updated movements and distances of Bas. EvBA attained 99.42% accuracy and reduced the computational time by 6.07%

Cai et al. [45] proposed an improved BA (ImBA) based on disturbance and forage strategies. The forage strategy was used to monitor the search direction of bats. The exploration capability of BA was enhanced through disturbance strategy. Zhu et al. [46] developed a quantum-based BA (QMBA) to enhance the convergence speed. QMBA utilized the statistical information of bats to produce the good quality solutions. QMBA was superior to BA and IBA in terms of accuracy

and exploration capability. Rekaby [47] developed a directed artificial BA (DABA). The frequency of waves is increased if bat found a prey. Otherwise, it is decreased. DABA attained approximately 10% improvement in performance as compared to BA and ABC algorithms. Kabir et al. [48] proposed a novel ABA (NABA) using Gaussian distribution and Rechenberg's mutation rule. Gaussian distribution was used to adjust the mutation size. Rechenberg's mutation rule was used to maintain balance between intensification and diversification. NABA performed better than BA. Topal and Altun [49] developed a dynamic virtual BA (DVBA). DVBA used two types of bats namely explorer and exploiter bats. DVBA was superior to the existing algorithms in terms of accuracy and reliability. Cai et al. [50] proposed a BA with Gaussian walk (BAGW) that utilized the local turbulence. The frequency and velocity were also modified to maintain the balance between exploration and exploitation. BAGW outperformed the existing variants of BA.

Zhou et al. [51] developed a cloud model BA (CMBA). In CMBA, pulse rate and loudness were modified. CMBA is superior to the existing algorithms. Cai et al. [52] devised a modified BA based on triangle-flapping strategy (BATF). These strategies were used to modify the velocity of bats. Al-Betar and Awadallah [53] proposed an island-based BA (iBA) to enhance the diversity. The population was decomposed into islands of bats. The best–worst migration rate was used to migrate the population from one island to other. iBA was evaluated on benchmark test problems and obtained better results than the other algorithms. Gan et al. [54] devised a new BA based on local search and inertia weight (ILWBA). The iterative local search was used to avoid the premature convergence. The inertia weight was used to modify the velocity of bats. The pulse rate and loudness were modified to maintain balance between exploration and exploitation. ILWBA provided better results than BA and DBA. Nawi et al. [55] introduced a Gaussian distribution in BA (BAGD) to generate the short step length. BAGD was tested on benchmark test functions and attained better performance than BA in terms of fitness value. Shan and Cheng [56] proposed an improved BA based on the covariance adaptive evolution (CMABA). This evolution was used to enhance the diversity of bats. CMABA outperformed the existing algorithms on benchmark test functions.

Kiełkowicz and Grela [57] presented two modifications in velocity update and new solution acceptance of BA (BA-VS). BA-VS was superior to the other algorithms. Yahya and Tokhi [58] presented a MABSA, which is based on the echolocation of bats. A bounce back strategy was used to eliminate the boundary exceeding problem. MABSA provided better accuracy and convergence rate than the other competitive algorithms. Jaddi et al. [59] developed a modified BA based on the structure and weights of artificial neural networks. This approach was known as BANN. Chaotic

functions were also added in BANN. BANN performed better performance than BA and ANN. Ghanem and Jantan [60] utilized a special mutation operator in BA (EBat) to evade the premature convergence. EBat outperformed the BA in terms of fitness value. Banati and Chaudhary [61] developed a multimodal variant of BA with improved search (MMBAIS). In MMBAIS, population of bats was decomposed into non-overlapping subpopulations. The movement of bats in these sub-populations towards the best local neighbor bat. The step size was used to update the position of bats precisely. MMBAIS attained 100% success rate for most of the benchmark functions. To improve the performance of MMBAIS, Chaudhary and Banati [62] introduced the weighted version of MMBAIS (wMMBAIS). The weighted difference between energy gain and spent was computed to select the prey. The proposed approach attainted significant improvement in performance.

Chaudhary and Banati [63] developed a swarm BA with improved search (SBAIS) algorithm. In SBAIS, the best bats were placed in one group. The other bats were placed in different groups according to their fitness value. SBAIS monitored the diversity of bats. If diversity was reduced to specified threshold value, then the random solutions were added in the bat's population. SBAIS was superior to the existing variants of BA. BA was combined with shuffled frog lapping algorithm (ShBA) to improve the performance of BA. Banati and Chaudhary [64] proposed an extension of ShBA (EShBA) to enhance their diversification capability. In EShBA, the best bats were selected to form a new group. The new formed group was used to intensify the best solutions. EShBA was superior to ShBA and BA. Jaddi et al. [65] developed a novel BA that utilized the Ring Master–Slave strategy and known as BARM-S. BARM-S decomposed the population into sub-populations (SPs) and evolved each sub-population independently. In master–slave strategy, the best solutions from SPs were sent to master SP. BARM-S outperformed the BA in terms of fitness value. Chaudhary and Banati [66] proposed a shuffled multi-population BA (SMPBA). The cooperation and shuffling strategies were utilized to preserve the information gain. The convergence rate of SMPBA was better than BARM-S and EShBA. Al-Betar et al. [67] investigated six different selection mechanisms to choose the best position of bat. Based upon these selection techniques, six variants of BA were developed and named as tournament BA (TBA), proportional BA (PBA), random BA (RnBA), exponential rank BA (ErBA), linear rank BA (LrBA), and global-best BA (GbBA). TBA was able to generate the better results than the other variants of BA on the most of benchmark functions.

Cai et al. [68] designed two variants of BA named as BA-PCA and BA-LBA, which are based upon the principal component analysis. The golden selection method was used to determine both correlation and generation thresholds.

BA-PCA and BA-LBA performed better than BA. Wang et al. [69] suggested eight different strategies to improve the performance of BA and known as MixBA. These strategies were used to modify the velocity, position and frequency of bats. Junaid et al. [70] proposed a modified BA (BASobol) based on Sobol sequence. The Sobol distribution was used to initialize bat's population. The inertia factor was added to modify the velocity of bats. BASobol was superior to BA. Huang and Ma [71] developed an integration strategy-based BA (IsBA) In IsBA, Gaussian functions having different variances were used to evade the local optima problem. IsBA was tested over benchmark test functions and attained superior performance to the other algorithms. The torus walk was used to develop the new variant of BA (TW-BA) [72]. The local and global search strategies were used to develop new variant of BA (LGCBA) [73]. Alsalibi et al. [74] developed a novel variant of BA (DMBA), which was based on the dynamic structure of membrane. DMBA maintained the population diversity of bats. DMBA has less computational time as compared to BA. Mashwani et al. [75] proposed a modified version of BA (M-BA) that utilized the position updating mechanism.

4.2 Binary BA

Mirjalili et al. [76] developed a binary variant of BA (BBA). In BBA, the velocity and position of bats are modified. They used V-shaped transfer function to map the continuous search space into binary search space. BBA was able to produce best solutions for both unimodal and multimodal test functions. BBA produced an optimal design of optical buffer. Rizk-Allah and Hassanien [77] presented a novel BBA (NBBA) to solve the knapsack problems. They used two stage search strategy. In the first phase, BBA was to find the best solutions. Thereafter, local search mechanism was used to avoid the solutions are being stuck in local optima. NBBA performed better than BBA. Sabba and Chikhi [78] developed a discrete BBA (BinBBA) to solve the multidimensional knapsack problems. They used sigmoidal function for mapping the continuous search space into binary space. BinBBA was superior to the other binary metaheuristics. Ma and Wang [79] investigated the influence of control parameters on convergence speed, global search ability, and precision of BBA.

Dahi et al. [80] used five different mapping functions to design the five variants of BBA. These are nearest integer-based BBA (NI-BBA), sigmoid function-based BBA (SF-BBA), Great value priority-based BBA (GVP-BBA), Angle modulation-based BBA (AM-BBA), and normalization-based BBA (N-BBA). Results revealed that NI-BBA and SF-BBA performed better than the other variants of BBA. Tawhid and Dsouza [81] developed a hybrid binary version of BA and PSO (HBBEPSO) to handle the feature selection problems. BA was used to explore the search space. PSO was used for exploitation. HBBEPSO was able to extract the optimal features for UCI machine learning datasets. Meraihi et al. [82] devised an improved chaotic BBA (ICBBA). The logistic and tent maps were used to figure out the frequency of bats. They used dynamic formulation to modify the loudness. ICBBA was able to provide optimal solution for QoS multicast routing problem. Huang et al. [83] developed a improved version of BBA (IBBA), which was based on neighborhood search. They used inertia weight factor to update positions of bats. Ravindra and Rao [84] presented an upgraded BBA (UBBA) for solving power grid network problem.

4.3 Chaotic BA

Jordehi [85] presented a novel variant of BA (CBA), which is based on chaotic map functions. They used eleven different chaotic maps. The loudness of bats was modified. CBA was able to eliminate the premature convergence. Lin et al. [86] proposed a chaotic levy flight BA (CLFBA) based on the concepts of levy flights and chaotic dynamics. CLFBA is an efficient algorithm to determine the optimal solution. Gandomi and Yang [87] proposed a chaos-based BA (CsBA). They used different chaotic maps to replace the control parameters of BA. Four different CsBAs were developed by modifying the frequency, pulse rate, loudness and position of bats. Thirteen different chaotic maps were used. It is observed from the experimental results that sinusoidal map-based CsBA performed better than the other three variants of BA.

Hamidzadeh et al. [88] developed a CBA based on the weighted SVDD (WSVDD-CBA). WSVDD-CBA was able to swap the local search into global search and vice versa. This proposed approach was used for segregation of data under imbalanced data. Xueting et al. [89] developed a global CBA (GCBA) to solve feature selection problem. The chaotic method was used to initialize the bat's population. GCBA eliminated the premature convergence. Afrabandpey et al. [90] utilized the chaos to develop the improved version of BA (CIBA). Chaotic sequences were used to initialize the control parameters of BA. CIBA performed better than BA.

4.4 Levy Flight BA

Liu and Chunming [91] introduced the behaviors of Levy flight (LF) in BA. They developed a new variant of BA and known as LFBA. The speed and position of bats were modified. LFBA outperformed the BA in terms of accuracy and convergence rate. Boudjemaa et al. [92] investigated fractional calculus to further enhance the performance of LFBA and called as Fractional LFBA (FLFBA). Levy distribution based random walk was used to conduct local search. The

velocity of bat was updated through fractional calculus. FLFBA was evaluated on test functions and achieved better performance than the other algorithms. Xie et al. [93] introduced a new LF variant of BA (DLFBA) based on differential operator and LF. A differential operator is added in BA to increase the convergence rate. LF was used to maintain the diversity in BA. The proposed algorithm was superior to the other Levy flight variant of BA.

Shan et al. [94] presented an improved version of BA (OBMLBA) that utilized the concepts of LF random walk and opposition based learning (OBL). OBL is used to enhance diversity in BA. OBMLBA was more efficient algorithm than the other algorithms. Jun et al. [95] presented a double sub-population LFBA (DLBA). They used dynamic switch strategy to maintain the balance between intensification and diversification in the sub-population of BA. LF model and dynamic weight model were used for position update in internal and external subgroups, respectively. DLBA performed better than the other algorithms. Li et al. [96] developed an improved BA (LAFBA) based on the concepts of adjustment factors and Levy flights. The inertia weight was used to modify the velocity of bats. The speed and accuracy of LAFBA was improved through adjustment factor.

4.5 Hybrid BA

Fister et al. [97] combined BA and differential evolution strategies (BA-DE) to improve the performance of BA. This hybrid approach modified the mechanisms of solution selection and new local solution generation using DE. This approach outperformed BA for high-dimensional benchmark problems. However, the computational complexity is not investigated for this approach. Yildizdan and Baykan [98] hybridized the ABC and BA to solve the optimization problems. The inertia weight was incorporated in BA to further improve the search ability. The hybrid approach was evaluated on benchmark test functions and found that BA-ABC provided better results than the BA and ABC. The contribution of BA (i.e., 92%) was much higher than ABC (i.e., 4%) in this hybrid approach. However, the time complexity of BA-ABC was title bit higher than ABC and BA. Wang and Guo [99] incorporated pitch adjustment operator of harmony search (HS) into BA for enhancing the exploitation ability of BA. This approach is called as BA-HS. The elitism scheme was also added in the hybrid approach. This modification improved the convergence speed of BA. The hybrid approach (i.e., BA-HS) outperformed the HS and BA in terms of convergence. Ghanem and Jantan [100] proposed a hybrid BA (BA/HS) to enhance the performance. The dynamic mutation operator of HS was used in BA. The pitch adjustment operator was not used in this approach.

The performance of this hybrid approach was better than HS, BA, and BA-HS.

Alihodzic and Tuba [101] developed a modified BA (MBA-DE) to solve the benchmark test problems. In MBA-DE, both BA and DE were hybridized to improve the performance. The mutation and crossover operators of DE were incorporated in MBA-DE. The modifications in loudness and pulse rate were also done. MBA was tested on the benchmark test functions and achieved the better results than BA-DE. Nguyen et al. [102] hybridized BA and ABC to improve the performance. The positions of worst bats were replaced with best artificial bees and vice versa. The communication strategy was developed for information transfer from BA to ABC. The hybrid algorithm (ABC-BA) obtained 78% and 11% more accurate results than BA and ABC on benchmark test functions. Rauf et al. [103] combined ABA with Sugeno fuzzy search (ASF-BA) to solve the constrained single-objective problems. ASF-BA was also tested to optimize the weights of feed forward NN. ASF-BA attained better classification accuracy than the BA. Fister et al. [104] proposed a hybrid BA (HBARF) that ensembles the DE and random forest (RF). HBARF attained better performance than BA. Yildizdan and Baykan [105] integrated modified BA (MBA) and DE (MBADE) to improve the search capabilities. MBA used modifications in BA to eliminate structural issues. Mutation phase of DE was used to modify the solutions obtained from MBA. MBADE was superior to MBA in terms of fitness value.

He et al. [106] integrated SA and Gaussian perturbations (GP) in BA to improve the convergence speed. The proposed algorithm was named as SAGBA. SA and GP were used to modify the velocity and position of bats. SAGBA performed better than the BA and other algorithms. Fister et al. [107] integrated DE and self-adaptive BA (SABA) to obtain the quality solutions. The proposed algorithm (HSABA) was evaluated on benchmark test functions and achieved superior performance than BA and SABA. Pan et al. [108] integrated a communication strategy of PSO in BA to solve numerical
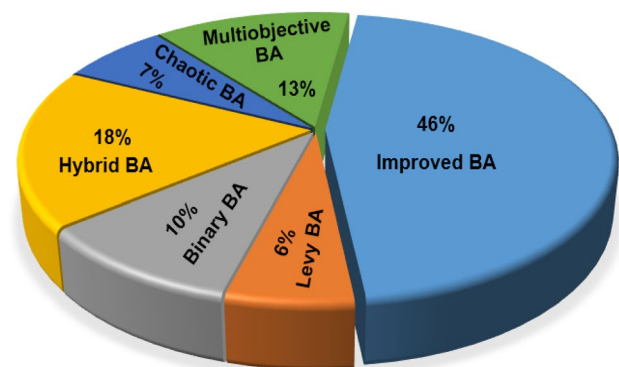

Fig. 5 Distribution of BA's Variants according to research articles

Table 2 Summarization of BA's variants

Category	Method	Depiction	Application	Performance	Ref
Improved	DBA	Modifications are done in pulse rate, loudness, local search mechanism, directional movement of bats	Numerical Problems	Better exploration, improved performance	[30]
	GBA	Doppler effect is employed to improve performance	Numerical Problems	Better efficiency	[31]
	NBA	Self-adaptive strategy is used to tackle the echos generate from Doppler effect	Design Problems	Good diversity and convergence	[32]
	ABA	Dynamic flight speed and directions are employed to improve the performance	Numerical Problems	Better accuracy, good convergence	[33]
	RBA	Recollection concept is added to enhance performance	Numerical Problems	Good convergence	[34]
	CVBA	Complex-value encoding scheme is employed	Numerical Problems	Better diversity, Improve performance	[35]
	CoBA	The probability updated population is used	Numerical Problems	Better solution quality	[36]
	MBA	Inertia weight factor is used to update velocity of bats	Numerical Problems	Better exploration	[37]
	QBA	Quaternion Representation scheme is employed	Numerical Problems	Better performance for high-dimensional problems	[38]
	MoBA	Pulse rate and loudness are modified	Numerical Problems	Better exploration	[39]
	BA-SM	Gaussian and Cauchy mutation are used to enhance performance	Numerical Problems	Improved performance	[40]
	IBA	Inertia weight factor and frequency modification are done in BA	Numerical Problems	Better exploration and exploitation	[41]
	ExBA	Variations in pulse rate and loudness are done	Numerical Problems	Better performance	[42]
	EBA	Modifications are done in velocity and position of bats	Numerical Problems	Better exploration and exploitation	[43]
	EvBA	Sound speed is used to modify the position of bats	Numerical Problems	Better accuracy, less computational time	[44]
	ImBA	Disturbance and forage strategies are employed	Numerical Problems	Improved performance	[45]
	QMBA	Quantum behavior of bats is used to improve the diversity	Numerical Problems	Better quality solution, avoid local optima	[46]
	DABA	Frequency is modified to change the direction of bats	Travelling Salesman Problems	Improved performance	[47]
	NABA	Mutation and Gaussian probability distribution are employed to improve the performance	Numerical Problems	Better exploration and exploitation	[48]
	DVBA	Rule-based search is used to balance the exploration and exploitation	Numerical Problems	Better convergence	[49]
	BAGW	Gaussian walk is employed in BA	Numerical Problems	Better exploration and exploitation	[50]
	CMBA	Cloud model is used to enhance the performance	Numerical Problems	Robustness, effective	[51]
	BATF	Triangle-flapping strategies are used to update the velocity	Numerical Problems	Improve robustness	[52]

Table 2 (continued)

Category	Method	Depiction	Application	Performance	Ref
	iBA	Island model is employed in BA to enhance the diversity	Economic Load dispatch	Better exploitation	[53]
	ILWBA	Inertia weight and local search are integrated in BA	Numerical Problems	Better accuracy, computational speed, convergence rate	[54]
	BAGD	Gaussian distribution is introduced in BA	Numerical Problems	Good accuracy	[55]
	CMABA	Adaptive covariance evolution is added in BA	Numerical Problems	Better solution quality	[56]
	BA-VS	Modifications are done in velocity and positions of bats	Numerical Problems	Better solution quality	[57]
	MABSA	Bounce back strategy is used to enhance the performance of BA	Numerical Problems	Good accuracy, Better convergence rate	[58]
	BANN	Chaotic maps and ANN are integrated in BA	Time series prediction problem	Good accuracy, better convergence	[59]
	EBat	Mutation operator is employed to improve diversity of BA	Numerical Problems	Good solution quality	[60]
	MMBAIS	Multi-modal concept is incorporated in BA. The information of best neighbor is shared among the bats	Numerical Problems	Avoid premature convergence, better exploration	[61]
	wMMBAIS	Weighted approach is employed to enhance the exploration	Numerical Problems	Good solution quality	[62]
	SBAIS	Best bats are kept in one group and used them to improve the search process	Numerical Problems	Superior performance	[63]
	EShBA	An additional evolution step is employed to share information among bats	Numerical Problems	Better convergence speed	[64]
	BARM-S	Ring master–slave strategy was employed to maintain the balance between intensification and diversification	Numerical Problems	Better solution quality	[65]
	SMPBA	Population partitioning and cooperation concepts are added in BA	Numerical Problems	Preserve information gain	[66]
	TBA, PBA, RnBA, ErBA, LrBA, GbBA	Based on six selection mechanisms, different variants of BA are developed	Numerical Problems	Better performance	[67]
	BA-PCA, BA-LBA	Principal component analysis is employed to enhance the diversity	Numerical Problems	Better performance	[68]
	MixBA	Multiple autonomous selection strategy is used	Numerical Problems	Good solution quality	[69]
	BASobol	Sobal distribution is used to initialize the bat's population. The velocity of bats is modified through Chaotic inertia weight	Numerical Problems	Global solution	[70]
	IsBA	Integration strategy is used to eliminate premature convergence	Numerical Problems	Improved performance	[71]
	TW-BA	Torus walk is use to improve the local search ability of BA	Numerical Problems	Good solution quality	[72]

Table 2 (continued)

Category	Method	Depiction	Application	Performance	Ref
	LGCBA	Both local and global search are integrated in BA to improve the performance	Numerical Problems	Better convergence speed, high precision	[73]
	DMBA	The membranes are dynamically evolved through separation and integration rules	Numerical Problems	Better accuracy, convergence speed	[74]
	M-BA	The impact of temperature is considered to evaluate the sound speed, varying wavelength is used to find out the prey	Numerical Problems	Better exploration, accuracy	[75]
Binary	BBA	V-shaped transfer function is used to map the continuous search space to binary space	Optical Buffer Design	Fast convergence rate	[76]
	NBBA	Two phase search strategy is used	0–1 knapsack Problems	Improved convergence rate	[77]
	BinBBA	Sigmoidal transfer function is employed	Multidimensional knapsack problems	Better performance	[78]
	NI-BBA, SF-BBA, N-BBA, AM-BBA, GVP-BBA	Five different transfer functions are used to design the variants of BBA	Antenna Positioning Problem	Integer and sigmoid function provides better performance	[80]
	HBBEPSO	BBA and PSO are hybridized to enhance the performance	Feature Selection Problem	Optimal feature set	[81]
	ICBBA	Chaotic maps and loudness parameter are used to improve the performance	QoS Multicast Routing	Better exploration	[82]
	IBBA	Dynamic inertia weight is employed in BBA to improve the performance	Numerical, Knapsack Problems	Avoid premature convergence	[83]
	UBBA	Loudness and pulse rate are modified	Phase measurement units allocation problem	Better performance	[84]
Chaotic	CBA	Eleven chaotic maps are employed	Numerical Problems	Prevent premature convergence	[85]
	CLFBA	Levy flight and chaotic dynamic strategies are used to enhance the performance of BA	Numerical Problems	Easy implementable and efficient	[86]
	CsBA	Chaotic maps are used to improve the reliability	Numerical Problems	Enhance the solution quality	[87]
	WSVDD-CBA	Weight and chaotic functions are used for interchanging the local and global searches	Classification Problems	Better accuracy, recall and precision	[88]
	GCBA	Chaotic sequences are used to initialize the population	Classification Problems	Prevent premature convergence	[89]
	CIBA	The control parameters of BA are initialized through chaos sequences	Numerical Problems	Better performance	[90]
Levy Flight	LFBA	Levy flight behaviors are added into BA for enhancing its performance	Numerical Problems	Better accuracy	[91]
	FLFBA	Fractional calculus is used to update the velocity. A Levy distribution based random walk is used to conduct local search	Numerical Problems	Fast convergence	[92]
	DLFBA	Differential operator and Levy flight are used in BA	Numerical Problems	Fast convergence, better exploration	[93]
	OBMLBA	Opposition learning and Levy flight are integrated in BA	Numerical Problems	Fast convergence	[94]

Table 2 (continued)

Category	Method	Depiction	Application	Performance	Ref
	DLBA	Dynamic weight and Levy flight models are used to update the positions of bats. The mutation probability is used to maintain the diversity	Numerical Problems	Better accuracy, mitigate premature convergence	[95]
	LAFBA	Levy flights and adjustment factors are used to maintain the balance between exploration and exploitation capabilities	Engineering Problems	Better performance	[96]
Hybrid	BA-DE	Differential evolutional strategies are used to modify the solutions obtained from BA	Numerical Problems	Improved performance	[97]
	BA-ABC	ABC is employed to enhance the diversity	Engineering Design Problems	Better search capability	[98]
	BA-HS	Pitch adjustment operation is used to update the position of bats	Numerical Problems	Better performance	[99]
	BA/HS	HS is combined with BA to enhance the convergence speed	Numerical Problems	Evade local optima problem	[100]
	MBA-DE	Mutation and crossover operators of DE are used to enhance the performance of BA	Numerical Problems	Improved convergence, robustness	[101]
	ABC-BA	Communication strategy is established for data transfer from BA to ABC	Numerical Problems	Good solution quality	[102]
	ASF-BA	Adaptive inertia weight and fuzzy logic are incorporated in BA	Classification Problems	Better classification accuracy	[103]
	HBARF	DE strategies are used to generate ten different solutions. Thereafter, random forest regression is applied on developed solutions	Numerical Problems	Good solution quality	[104]
	MBADE	Mutation phase of DE is employed to enhance the performance	Numerical Problems	Good solution quality	[105]
	SAGBA	Gaussian perturbations and simulated annealing are integrated in BA	Numerical Problems	Fast convergence rate, good accuracy	[106]
	HSABA	DE is introduced in self-adaptive BA	Numerical Problems	Good solution quality	[107]
	BA-PSO	PSO is used to replace the worst individuals in BA	Numerical Problems	Better accuracy	[108]
	HyBA	Extremal optimization algorithm is used to eliminate local optima problem	Numerical Problems	Longer computational time, better accuracy	[109]
	HS-BA	Pitch adjustment operator is used to update positions of bats	Numerical Problems	Evade premature convergence	[110]
	BADE	DE is used to enhance performance of BA	Numerical Problems	Efficient, robust	[111]
	BA-IWO-GA	IWO and GA are integrated in BA	Numerical Problems	Better accuracy	[112]
Multi-objective	MOBAT	BA is extended to handle MOO problems	Benchmark test functions	Diversity of Pareto Fronts	[113]
	MOShBAT	ShBAT is extended to deal MOO problems	Power System Problem	Better performance	[114]
	NSBAT-II	Pareto non-dominance is used to extend BA into multiobjective version of BA	Phthalic Anhydride Reactor Problem	Fast convergence	[115]

Table 2 (continued)

Category	Method	Depiction	Application	Performance	Ref
	MOB-ARM	MOBA is used to solve association rule mining problem	Numerical association rule mining	Good quality rules	[116]
	MOBA	BA is extended to deal multi-objective optimization. Wire length and dead space are to be minimized	VLSI Design Problems	Better performance	[117]
	MOIBA	Pareto-dominant concept is used to confirm inequality constraints	Emission Power Loss Problems	Optimal fuel cost, low power loss	[118]
	MaOBAT	Dominance rank is used to figure out dominance relationship. Reference points are used to maintain good convergence	Numerical Problems	Distributed Pareto Fronts	[119]
	MOMBA	Constrained Pareto-dominant approach is used to enhance the diversity	Power Problems	Distributed Pareto Fronts	[120]
	MOBATD	Decomposition approach is incorporated in MOBA	Non-linear Programming Problem	Diverse Pareto Fronts	[121]
	IMOBA	Candidate generation, competitive learning, and best solution selection strategies are incorporated in BA to handle MOO	Portfolio Optimization Problem	Good solution quality, fast convergence	[122]

problems. The worst individuals of BA were replaced with best individuals of PSO and vice versa. BA-PSO was able to provide better accuracy than BA and PSO. Liu et al. [109] performed three amendments in BA to further improve its performance. They devised a hybrid BA (HyBA) that utilized the extremal optimization algorithm to eliminate the local optima problem. However, HyBA is a complex algorithm. Guo et al. [110] devised a hybrid algorithm that utilized the pitch adjustment operation of HSA to modify the positions of bats. The hybrid approach, HS-BA was superior to BA, PSO, and HS in term of convergence speed. Ming et al. [111] presented a hybrid BA with DE, named BADE to solve the constrained problems. Pravesjit [112] developed a hybrid BA with IWO and GA, called BA-IWO-GA to deal the numerical problems. GA was used to expand the bat's population. IWO was used to compute the number of seed. These seeds were used to generate the clones. BA-IWO-GA was superior to BA, GA, and IWO. Beside these approaches, the other metaheuristic algorithms can be hybridized with BA to enhance its performance.

4.6 Multi-objective BA

Yang [113] presented an extension of BA (MOBAT) to deal multiobjective optimization (MOO) problems. MOBAT was evaluated on benchmark test functions and achieved better Pareto fronts. Yammani et al. [114] developed a multiobjective shuffled BA (MOShBAT) to handle the planning of generators. Crowding distance and non-dominated sorting mechanisms were added in ShBAT. MoShBAT was able to generate distributed Pareto Fronts. Prakash et al. [115] used the concepts of elitism and non-dominance to develop multiobjective BA (NSBAT-II). The performance of NSBAT-II was tested on real-life reactor problem and showed better convergence than NSGA. Heraguemi et al. [116] devised a multiobjective BA (MOB-ARM) to solve the association rule mining problem. MOB-ARM was able to retrieve important and believable rules. Laudis et al. [117] developed an extended version of multiobjective BA (MOBA) to solve VLSI problem. Chen et al. [118] proposed a new multiobjective improved BA (MOIBA). Pareto-dominance concept was added in MOIBA. The non-dominated sorting and crowding distance were used. MOIBA was tested over electrical problem. MOIBA was able to generate the diverse Pareto Fronts.
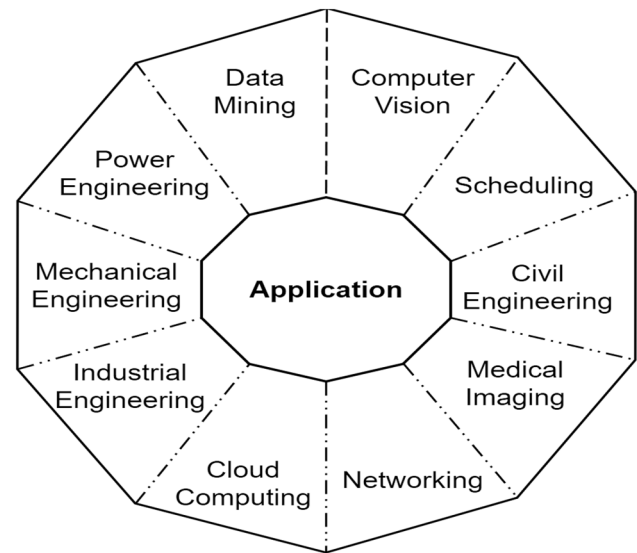
Perwaiz et al. [119] proposed a many objective BA (MaO-BAT). The dominance rank was used to establish relationship of dominated solution. Non-dominated solutions were selected on dominance relationship. MaOBAT attained better convergence rate that the other algorithms. Han et al. [120] presented a new multiobjective MBA (MOMBA) to solve the power flow problem. In MOMBA, Pareto-dominance approach was used to enhance the exploration capability. MOMBA was able to generate diverse Pareto fronts.

Table 3 Modification in control parameters and encoding schemes used in BA

Ref	Method	Pulse rate	Loudness	Frequency	Encoding
[30]	DBA	✔	✔	✔	✗
[31]	GBA	✗	✗	✔	✗
[32]	NBA	✗	✗	✔	✗
[33]	ABA	✗	✗	✔	✗
[34]	RBA	✗	✗	✔	✗
[35]	CVBA	✗	✗	✗	✔
[38]	QBA	✗	✗	✗	✔
[39]	MoBA	✔	✔	✗	✗
[40]	BA-SM	✗	✗	✔	✗
[41]	IBA	✗	✗	✔	✗
[42]	ExBA	✔	✔	✗	✗
[44]	EvBA	✗	✗	✔	✗
[47]	DABA	✗	✗	✔	✗
[49]	DVBA	✗	✗	✔	✗
[50]	BAGW	✗	✗	✔	✗
[51]	CMBA	✔	✔	✗	✗
[53]	iBA	✔	✔	✗	✗
[54]	ILWBA	✔	✔	✗	✗
[56]	CMABA	✗	✗	✔	✗
[57]	BA-VS	✔	✔	✗	✗
[69]	MixBA	✗	✗	✔	✗
[73]	LGCBA	✗	✗	✔	✗
[74]	DMBA	✗	✗	✔	✗
[75]	M-BA	✗	✗	✔	✗
[82]	ICBBA	✗	✔	✔	✗
[84]	UBBA	✔	✔	✗	✗
[85]	CBA	✗	✔	✗	✗
[87]	CsBA	✔	✔	✔	✗
[93]	DLFBA	✔	✔	✔	✗
[95]	DLBA	✔	✔	✗	✗
[101]	MBA-DE	✔	✔	✗	✗

Fig. 6 Applications of BA

indicates the corresponding control parameters is used in the respective algorithm. ✗ indicates it has not used.

5 Applications

BA has been widely used in various engineering domains. The appropriate use of control parameters and population initialization in BA can help to solve the real-life problems in an effective manner. The applications of BA are mainly classified into civil engineering, power engineering, mechanical engineering, image processing, bioinformatics, data mining, industrial engineering, software engineering, and scheduling. Figure 6 shows the applications of BA in different engineering domains.

5.1 Civil Engineering

Ahmadianfar et al. [123] used IBA to solve the hydropower operations of multireservoir systems. They used mutation strategy to improve the performance of BA. The performance of IBA was tested on four and ten-reservoir systems. IBA outperformed the liner programming solvers in terms of fitness functions. Ethteram et al. [124] investigated BA to optimize the reservoir operation in dam. The performance of BA was evaluated on two well-known dams of Iran. BA provided lowest value of vulnerability index and highest values of resiliency and reliability indices. However, the convergence speed of BA is much slower than the other algorithms. Bozorg-Haddad et al. [125] applied BA to evaluate the performance of reservoir operations of Karoun-4 reservoir system. BA

Sheah and Abbas [121] developed a multiobjective BA (MOBATD) based on decomposition approach. The dominance used to select the leaders for covering less populated regions and evade the premature convergence problem. MOBATD provided diverse Pareto fronts. Jiang et al. [122] developed an improved MOBA (IMOBA) to deal portfolio problem. They used three different modification strategies in IMOBA. IMBOA improved convergence speed and good solution quality.

According to research articles mentioned in this study, the distribution of BA's variants is depicted in Fig. 5. Table 2 shows the summarization of BA's variants. Table 3 depicts the modifications done in control parameters and encoding schemes used in various variants of BA. In Table 3, ✔

was compared with GA and linear programming. Results revealed that BA was able to provide the optimal solution for reservoir problem. Bath et al. [126] introduced the local search into BA, called blended bat algorithm (BLBA). BLBA was used to optimize the design of retaining wall. The weight and cost were utilized in the design of fitness function. BLBA saved the design cost from 18 to 20% as compared to the traditional technique [127]. Farzin et al. [128] used BA to design the open channels for flood control. The channel construction cost was used as a fitness function. BA outperformed the existing algorithms in terms of cost and convergence.

Talatahari and Kaveh [129] improved BA by dynamically updating the average loudness of bats. They have also modified the echolocation parameters of bats. The improved BA was applied on two truss optimization problems (i.e., 244-bar and 1042-bar). IBA obtained the best results than the GA, PSO, and BA in terms of weight and number of analyses. Yancang and Zhen [130] suggested modifications in population initialization and speed computation. The learning factor and inertia weight were used to improve the search capability of BA. The modified BA was tested on 10, 25, and 72 bar truss problems. This approach attained the optimal solutions as compared to HS and GA. Kaveh and Zakian [131] proposed scale factor to improve the positions of bats. They applied the modified BA to optimize the skeletal structures. The modified BA achieved the better results than HS, FA, and CS in terms of design weight. Aalimahmoody et al. [132] used a feed forward neural network to compute the compressive strength of concrete. BA was used to determine the control parameters of ANN. This model was tested on 1030 concrete samples and attained the mean squared error of 27.64. Su et al. [133] developed a modified directional BA (MDBA) for damage identification of beam and truss type bridges. An elimination scheme was proposed to enhance the intensification capability of BA. MDBA provided better convergence and accuracy as compared to PSO, DE, and BA.

5.2 Data Mining

Nakamura et al. [134] used BBA to solve the feature selection problem. BBA was applied on UCI machine learning datasets and attained the approximately 2% improvement in accuracy obtained from other binary metaheuristics. However, the computational speed of BBA was little bit higher than the other algorithms. Taha et al. [135] hybridized BA with Naïve Bayes classifier (BANB) for solving the feature selection problem. BANB was evaluated on UCI machine learning datasets. Results revealed that BAND outperformed the other metaheuristics in terms of number of features and classification accuracy. The computation time of BANB was

not investigated. Rodrigues et al. [136] developed a feature selection technique that utilizes the concepts of BA and optimum-path forest (OPF). They used transfer functions to map the continuous values into binary values. The binary BA was used to select the feature. The proposed approach was tested on six datasets. It is observed that the hyperbolic tangent transfer function was able to extract more appropriate features than the Sigmoid function.

Alihodzic et al. [137] modified the BA by incorporating the extreme learning machine. The proposed hybrid approach was known as UBA-ELM. UBA-ELM was used for data classification. The performance of UBA-ELM was better than the existing algorithms in terms of root mean square error, training time and number of hidden nodes. Leke and Marwala [138] hybridized BA with deep learning technique for the estimation of missing data. The accuracy obtained from the hybrid approach is better than BA and other deep learning techniques. However, it suffers from high computational time. Talal [139] used BA and PSO to train RBF network for data classification. The weights of RBF network computed from BA were better than PSO. BA provided better convergence and training time than the PSO. Cheruku et al. [140] combined the rough set and BA, called RST-BatMiner for fuzzy classification. Rough set was used to select the best features. BA was used to generate the fuzzy rules. The boosting technique was used to improve accuracy of fuzzy rules. This approach was evaluated on six datasets and yielded better accuracy than the Fuzzy rule miner. Taha and Tang [141] used BA for attribute reduction. Thirteen benchmark datasets were used to demonstrate the performance of BA. Results depicted that BA outperformed the classical feature selection techniques in terms of features and accuracy. BA was also used for record deduplication [142].

Komarasamy and Wahi [143] used BA to resolve the problems associated with K-Means clustering method. BA-based clustering technique eliminated the problem of K-Means. The proposed clustering technique achieved better efficiency than the classical clustering techniques. Sood and Bansal [144] proposed a clustering technique that utilized the concepts of K-Medoids and BA. The echolocation behavior of BA was used to eliminate problem associated with K-Medoids. The proposed clustering technique outperformed the classical clustering techniques in terms of performance measures. However, the computational complexity of proposed technique was higher than the other techniques. Aboubi et al. [145] proposed a BA-based clustering technique (BAT-CLARA) for large datasets. K-Medoids was used to construct the clusters. BAT-CLARA performed better results than the other clustering techniques. Heraguemi et al. [146] proposed a multi-swarm BA with three cooperative strategies to tackle the rule discovery problem. Ring, Master–Slave and hybrid strategies were used to generate the efficient association rules. The proposed approach

outperformed the competitive algorithms in terms of rule quality and computational time.

5.3 Computer Vision

Zhang and Wang [147] proposed a modification in BA (MBA) by incorporating the mutation operator. MBA was used to mutate bats during the position updating mechanism. MBA was applied on image matching problem. MBA was able to provide the better performance than the BA and other competitive algorithms. Alihodzic and Tuba [148] developed an improved BA (IBA) that includes the basic concepts of DE and ABC. IBA was applied on image thresholding problem. IBA outperformed PSO, DE, and BA in terms of convergence speed and accuracy. Alsalibi et al. [149] developed a membrane-inspired BBA (MIBBA) for facial feature selection. The evolution and communication rules of membrane computing were incorporated into BBA. Great Deluge Algorithm was added in MIBBA to enhance the intensification capability. MIBBA was able to provide the better face recognition rate than the other techniques. Akhtar et al. [150] employed BA to estimate the pose of human being. Statistical background subtraction and GMM were used to extract the human body. The performance of BA outperformed the competitive algorithms in terms of most appropriate pose error.

5.4 Medical Imaging

Alomari et al. [151] proposed a filter such as minimum redundancy maximum relevancy and wrapper method such as BA, known as MRMR-BA for selection of gene in microarray dataset. MRMR was used to extract the important genes from microarray dataset. Thereafter, BA was used to determine the important genes from the extracted genes. The performance of MRMR-BA was demonstrated on three datasets and attained better classification accuracy than the other algorithms. Mishra et al. [152] developed a BA to update the weights of ANN classifier. The proposed approach evaluated on breast cancer and lung cancer datasets. The proposed approach attained the classification accuracies of 91.7% and 96.3% for breast cancer and lung cancer, respectively. Lu et al. [153] designed an automatic brain detection system that utilized the concepts of ELM. The ELM was optimized through BA. This approach computed the entropies from subbands that were obtained from 2D discrete wavelet transform. The proposed approach attained the specificity of 93.89% and accuracy of 98.33% for brain images. Lu et al. [154] combined deep learning technique and BA to detect the abnormal brain in MRI images. The biases and weights of ELM were optimized through chaotic BA. The fine-tuned ELM model was used to extract the abnormal brain. The proposed approach provided the

sensitivity of 97.1% and accuracy of 96.4%. Kora and Kalva [155] designed an improved BA (IBA) to detect abnormalities in the heart using ECG signals. The noise was removed from the ECG signals and extract the features from the ECG signals. The extracted features were applied in the neural network classifier. IBA outperformed the other techniques in terms of classification accuracy.

5.5 Scheduling

Marichelvam et al. [156] investigated the use of BA to solve the multistage flow shop scheduling problem. This approach was tested on benchmark test problems and attained the better results than PSO and GA. Luo et al. [157] proposed a discrete BA (DBA) for flow shop scheduling problem. The scheduling problem was decomposed into small sub problems. The neighborhood search was incorporated into DBA for further enhance their performance. DBA was applied on twenty-nine benchmark problems. The performance of DBA outperformed the competitive algorithms in terms of solution quality. Tosun and Marichelvam [158] designed a hybrid BA to figure out flow shop scheduling problem. The local search was integrated into BA. Results revealed that the proposed algorithm was able to solve this problem in an efficient and effective manner. Marichelvam and Prabaharam [159] developed a BA to minimize makespan and flow time in scheduling problem. The overall improvement obtained from BA was more than 20% as compared to PSO, ACO, and GA, and SA. Xie et al. [160] introduced a differential levy BA (DLBA) to tackle the flow shop problem. The levy light was integrated in DLBA to transform the continuous space into discrete space. The neighborhood search was used to eliminate the local optima problem. The effectiveness of DLBA was evaluated on benchmark test problems and attained the better results than the other algorithms. Dao et al. [161] integrated the concepts of parallel processing and communication strategy in BA. The proposed approach attained 2% improvement in the best known solution when it is compared with BA.

Musikapun and Pongcharoen [162] developed a BA-based scheduling tool (BAST) to resolve the multi-machine scheduling problem. BAST was used to minimize the tardiness and earliness costs. BAST attained 8.37% improvement in the overall performance as compared to the other algorithms. Malakooti et al. [163] implemented BA to handle the single objective and multiobjective multiprocessor scheduling problems (MSP). For single objective MSP, BA was used to minimize the makespan and tardiness independently. In multiobjective MSP, both objective were simultaneously optimized through BA. BA outperformed the competitive algorithms by 11.12% for makespan and by 23.97% for tardiness. Talafuse and Pohl [164] developed a BA to handle

the redundancy allocation problem. The performance of BA was demonstrated on benchmark test problems. BA outperformed the competitive algorithms in terms of system reliability. However, ACO performed better than BA for 13 instances. Fister et al. [165] introduced a method for planning the sport training sessions. BA was used to design the algorithm. The proposed method was helpful to coaches for planning the training sessions for upcoming competitions. Khan et al. [166] designed a screening method for company workplaces. They used Fuzzy BA to determine the cluster of workplaces. Three different clusters of workplaces were generated on the basis of health risk. Results showed the fuzzy BA was able to reduce the computational time for screening the workplaces.

Osaba et al. [167] presented a discrete BA to handle both symmetric and asymmetric traveling salesman problem (TSP). An improvement was done in the structure of BA. The proposed algorithm was evaluated on thirty-seven test instances. The proposed algorithm performed better performance than the competitive algorithms for twenty-two test instances. Saji and Riffi [168] proposed a new modification in discrete BA to solve TSP. The modified approach was evaluated on forty-one symmetric benchmark test problems. This approach was able to obtain the optimal solutions over 30 runs for all test instances.

5.6 Power Engineering

Bora et al. [169] investigated single and multi-objective BA to tackle the brushless DC motor wheel problem. The efficiency obtained from single-objective BA was 95.23%. The power system stabilizers (PSS) can be considered as optimization problem. BA was used to solve PSS problem [170]. BA provided the better performance than the other algorithms. Peres et al. [171] investigated BA, ACO, and GA to solve the tuning problem of PSS. These algorithms were tested on New England test system. BA provided better results than the ACO and GA in terms of damping ratio. Sambariya and Prasad [172] designed a PSS by using BA. BA was used to optimize the control parameter of PSS. BA outperformed the other algorithms in terms of speed response and stability. Sathya and Ansari [173] developed a BA-inspired dual mode PI controller. The developed PI controller was compared with the five conventional PI controller. It was found that the developed PI attained better steady state response and transient [174].

Sakthivel et al. [175] used BA to solve the economic load dispatch problem (ELDP). The control parameters of ELDP was optimized through BA. BA outperformed the conventional techniques in terms of optimal cost and convergence time. Bestha et al. [176] presented BA to handle the ELDP with valve point loading. BA obtained the optimal solution for all the test systems. BA attained 8121.86 R/Hr, and

10,123.69 R/Hr for 850 MW and 1050 MW load systems, respectively. Biswal et al. [177] used a BA to solve ELDP. The performance of BA was evaluated on three different thermal power units. BA took 2.537 s to obtain the optimal solution as compared to PSO. BA attained better results than the competitive algorithms. Ramesh et al. [178] used BA to solve both ELDP and emission dispatch problem. BA was tested on six different power systems. BA provided better convergence, efficiency, and features than the competitive algorithms. Niknam et al. [179] developed a multiobjective self-adaptive learning BA (MOSALBA) to solve ELDP. The chaos-based strategy was used to generate the initial population. They used crowding mechanism for uniform distribution of Parteo-optimal solution. The proposed approach performed better than the other approaches. However, the proposed approach was not evaluated in terms of transient stability.

Latif and Palensky [180] modified BA to handle the ELDP. The concepts of inertia weight and anti-predatory were incorporated into BA to enhance their exploration and exploitation capabilities. The modified BA (MBA) was applied on five and six-generator test systems and provided superior performance than the GA, PSO, and BA. The optimal size of battery energy storage (BES) is required for renewable energy sources. Bahmani-Firouzi and Azizipanah-Abarghooee [181] utilized BA to optimize the size of BES. The load demand and operating reserve were used as the objective function for BA. BA was able to provide the remedial schemes for minimum cost dispatches. Eltamaly et al. [182] proposed a scanning BA strategy to track peak load of photovoltaic energy systems (PVES). The proposed approach was able to reduce the convergence time by 566% as compared to the standard strategy. BA was used to determine the maximum power of PVES under partial shading [A61, A63] and dynamic partial shading conditions [184]. Niknam et al. [186] proposed an enhanced BA (EBA) to determine the supply equilibrium for generating companies. The self-adaptive mechanism was also introduced in EBA to improve the exploration capability. EBA was able to link the bidding price with bidding quantity.

Tamiru and Hashim [187] developed the fuzzy models to determine the exergy destruction variations present in various components of gas turbine. The training of model was done through BA and linear model tree. The proposed model can be used as a promising tool in the real-life scenario [189]. Kotteeswaran and Sivakumar [188] presented a BA for fine tuning of control parameters of PI controller of coal gasifier. This controller has five inputs and four outputs. LFBA was used to optimize the control parameters of gasifier. The proposed approach provided better response than the other algorithms. Kashi et al. [190] developed a BA to optimize the fuel management operation for nuclear reactor. They used peak power factor and multiplication factor for

designing the fitness function. BA was able to provide the optimal solutions for fuel optimization problem.

5.7 Industrial Engineering

Zhou et al. [191] hybridized BA and path relinking (PR) to tackle the vehicle routing problem (VRP). This proposed hybrid approach was known as HBA-PR. PR was used to determine local solutions. HBA-PR was evaluated on twelve instances from three different benchmark test problems. HBA-PR was able to generate the quality solutions for VRP [192]. Ochoa et al. [193] integrated BA and data mining to solve the group travelling problem. This approach was evaluated on three different parks of Chihuahua. Results revealed that the hybrid approach provided 91.72% improvement in solution quality as compared to random selection. Taha et al. [194] designed an adaptive BA (ABA) to tackle the capacitated VRP. ABA was tested on nine benchmark test problems and attained high précised solutions than the GA and BA. Dapa et al. [195] studied the performance of BA, Frog leaping algorithm and GA on facility layout problem (FLP). He et al. [196] designed an improved BA (IBA) to resolve the layout planning problems of medical sites and urban facilities. IBA provided better convergence than the BA. BA was also used to solve the single-row FLP [197]. The control parameters of BA were determined through the experimentation. BA was evaluated on six different test problems. BA provided quality solutions as compared to the competitive techniques.

Carbas and Hasancebi [198] used BA to optimize the design of steel frames. The main objective is to minimize the weight of frame and final cost. BA was able to provide the optimal design with least cost and weight [199]. Gholizadeh and Shahrezaei [200] studied BA to optimize the placement of steel frames within walls. The columns of frame, cross sections of beams, thickness and placement of plate walls were optimized through BA. The results revealed the effectiveness of BA for placement of frames in walls. Hasancebi et al. [201] investigated the use of BA in structure optimization. BA was tested on three truss structures and one benchmark test problem. BA provided the optimal weights for three truss structures. Arora et al. [202] proposed a BA-Ziegler algorithm to determine the optimal parameter of PID. The proposed approach was evaluated on three different plants. It was found that the proposed approach outperformed ACO, PSO and HAS in terms of step response. Omar and Saida [203] developed a BA-inspired design approach for PID controller in automatic voltage regulator (AVR) system. BA was able to determine the optimal parameters for PID controller. BA outperformed PSO in terms of time specification.

5.8 Networking

Sur and Shukla [204] designed an adaptive and discrete BA to determine the appropriate route for graph-based road network. Xi et al. [205] proposed an improved BA (IBA) for path planning problem for UAV. B-spline curves were used to obtain the optimal path. IBA outperformed the conventional algorithms. Wang et al. [206] modified BA (MBA) to solve the path planning problem. In MBA, the mutation among bats during the solution updating mechanism. MBA provided the better convergence and robustness than BA. Li and Peng [207] proposed an improved BA (IBA) to solve the UCAV problem. IBA was able to locate multiple solutions for UCAV. Kiran and Reddy [208] proposed a bat-inspired protocol named as bat-termite for mobile adhoc network. The bat-termite provided superior performance than the existing protocols. Pal and Sethi [209] implemented BA-based routing protocol for cognitive radio adhoc network. The developed protocol was able to select reliable channel for optimal route construction.

BA was also used to design the cell formation in routing problem [210]. The movement between cells was considered as an objective function in BA. BA was able to determine the optimal route with minimum intercell movement. Goyal and Patterh [211] used BA to evade node localization problem in WSN. The bacterial foraging concept was introduced in BA to enhance their performance and known as modified BA (MBA). MBA performed better than BA in terms of computational time and success rate. However, MBA showed inferior performance than BA in terms of mean localization error. Kaur and Sharma [212] delved BA to determine the precarious nodes in WSN. They used an optimized routing protocol to lessen the probability of packet drop. BA-based protocol provided the 100% packet delivery as compared to the existing protocols. BA-based protocol consumed very less energy as compared to the others. Cao et al. [213] developed an improved LEACH protocol by using BA. The cluster heads were generated through the traditional LEACH. Thereafter, the cluster heads were optimized through BA-inspired local strategy. The proposed approach provided better energy utilization, network load and network life than the LEACH protocol.

The dynamic router node placement is major problem in wireless mash network. To resolve this problem, Lin et al. [214] developed a BA-based local search mechanism to determine the optimal solution. The weights were assigned to both client coverage and network connectivity. The proposed approach provided stable and reliable results than PSO. The community detection problem can be considered as an optimization problem. BA was used to solve the community detection problem [215]. The modular quality measure was used as a fitness function. The performance of BA was superior to the other techniques for small networks.

However, the performance of BA was not good for large networks. Imane and Nadjet [216] hybridized BA with tabu search for detecting the overlapping communities. The density of links was used as an objective function for this hybrid approach. The hybrid approach was tested on six real networks. The hybrid approach obtained the density value of 0.7030, which was greater than BA (i.e., 0.5276) for dolphins network.

5.9 Cloud Computing

Raghavan et al. [217] used BBA for scheduling workflow in cloud environment. The workflow consists of four different tasks. The resources were allocated to each task. The main objective of this problem was to minimize the processing cost. The proposed approach attained an overall fifty percent improvement as compared to the existing technique. Sharma et al. [218] utilized a BA to implement load balancing in cloud environment. Parallel processing toolbox was used to implement the proposed load balancing approach. The proposed approach outperformed the other techniques in terms of response time and number of tasks.

5.10 Mechanical Engineering

Suárez et al. [219] implemented BA for designing the robotic prototype. Thereafter, it was tested to determine the location of target under 3D static environment. The behavior of real and simulated robots was almost similar. Mallick and Ganguli [220] proposed two orthogonal arrays to produce nonlinear response surfaces. MOBA was used to optimize the design points for surfaces. MOBA reduced the vibration levels of edge flap by 73% in comparison with the standard design. Kumaravel and Kumar [221] developed a self-tuned PI controller that adapt the load impedance through back propagation algorithm. BA was used to improve the convergence speed. The dynamic response obtained from the proposed model was better than PSO-inspired PI controller. Bekdas et al. [222] employed BA to optimize the seismic structures of mass dampers. The damping ratio, period, and mass were optimized using BA. The proposed approach was applied on the structure of ten-story and attained better results than GA, PSO, and HS. Chakri et al. [223] developed an improved BA (IBA) for analysis of structural reliability. An adaptive penalty was introduced in IBA to determine the reliability index. IBA has less computational time. Wang et al. [224] designed a hybrid BA to solve the process planning problem. The local search strategies were incorporated in BA and improved the movement of bats. The hybrid BA was superior to GA, PSO, and SA.

Naderi and Khamehchi [225] developed two new designs to predict the water drive gas reservoirs. BA was used to optimize the number of wells, locations of well, perforation

thickness, and production rate. The proposed approach was able to provide better recovery factor. Osaba et al. [226] developed a discrete and IBA (DIBA) to solve the drugs distribution problem. The hamming distance was used to compute the difference among bats. DIBA attained better results on 18 datasets. The convergence of DIBA was better than competitive algorithms. The process of selecting the appropriate cities to conduct the event is considered as an optimization problem. Ba was used to solve the planning problem [227]. BA was evaluated on twenty different European countries and data collected from Facebook. BA showed the superior results than the other algorithms in terms of quality solutions. Liu et al. [228] integrated BA with double mutation operators to further enhance their performance. This approach was known as TMBA. TMBA was applied to solve the impact localization in plate structure of ship. TMBA was able to provide the quality solution. Kongkaew [229] investigated BA's variants to solve the single machine scheduling problem. These variants were evaluated on the benchmark test instances of OR-library. The quality solutions were obtained from BA's variants within less time duration. Sadeghi et al. [230] utilized a hybrid BA (HBA) to find out the optimal solution for vendor managed inventory problem. HBA was an efficient algorithm in comparison with GA and BA.

5.11 Miscellaneous

BA was use to envisage the price of copper [231]. The price estimation parameters were optimized through BA and predict the price. The root mean square error obtained from BA was better than the conventional prediction methods. Srivastava et al. [232] estimated the test effort using BA. Results revealed that the estimation obtained from BA was very closer to the actual test effort. Hong et al. [233] used support vector regression model to predict the motion of floating platform. Chaotic BA (CBA) was used to optimize the control parameters of support regression model. They also used an ensemble decomposition algorithm. The proposed approach was able to predict the floating platform motion in an effective and efficient manner. Koffka and Sahai [234] investigated the performance of BA, GA, and PSO for training neural network in e-learning environment.

Cincy and Jeba [235] combined both ABC and BA to extract the information from crowdsourcing systems. Random walk phase was also implemented in this hybrid approach. This approach provided better accuracy, convergence rate and cost than the competitive algorithms. Cui et al. [236] proposed an adaptive BA (ABA) to optimize the observation matrix. The dynamic strategy was designed to improve the convergence ability of BA. BA was able to reduce the reconstruction error as compared to the conventional techniques. Natarajan et al. [237] studied the

Table 4 Summary of BA's applications

Application	Problem	Algorithm	Reference
Civil Engineering	Multireservoir Systems	BA, IBA	[123–125]
	Cantilever Retaining Wall	BA, BBA	[126, 127]
	Open Channels for Flood Control	BA	[128]
	Optimization of Truss Structure	IBA	[129, 130]
	Optimization of Skeletal Structure	EBA	[131]
	Compressive Strength of Concrete Structure	BA-ANN	[132]
	Structural Damage Identification	MDBA	[133]
Data Mining	Feature Selection	BBA, BANB, BA-OPF	[134–136]
	Data Classification	UBA-ELM, BA, RST-BatMiner	[137–142]
	Clustering	BA, BAT-CLARA	[143–145]
	Association Rule Mining	BA	[146]
Computer Vision	Image Matching	MBA	[147]
	Image Thresholding	IBA	[148]
	Face Recognition	MIBBA	[149]
	Human Pose Estimation	BA	[150]
Medical Imaging	Cancer Classification	MRMR-BA	[151]
	Microarray Data Analysis	ELM-BA	[152]
	Brain Detection	CBA	[153, 154]
	Myocardial Infarction	IBA	[155]
Scheduling	Flowshop Scheduling	BA, DBA, DLBA	[156–161]
	Multi-product Scheduling	BA	[162, 163]
	Allocation Problem	BA, Fuzzy BA	[164–166]
	Travelling Salesman Problem	BA, DBA	[167, 168]
Power Engineering	Power Stabilizer Problem	BA, MOBA	[169–172]
	Load Frequency Control	BA	[173, 174]
	Economic Load Dispatch	BA, MOSALBA, MBA	[175–180]
	Battery Energy Storage	BA	[181]
	Photovoltaic Energy Systems	BA	[182–185]
	Supply of electricity market	EBA	[186]
	Gas Turbine	BA, LFBA	[187–190]
Industrial Engineering	Vehicle Routing Problem	BA, ABA, HBA-PR	[191–194]
	Facility Layout Problem	BA, IBA	[195–197]
	Steel Frame Optimization	BA	[198–201]
	PID Parameter Tuning	BA	[202, 203]
Networking	Path Planning	BA, IBA, MBA	[204–207]
	Routing Protocol	BA, MBA	[208–214]
	Community Detection	BA	[215, 216]
Cloud Computing	Workflow Management	BBA	[217]
	Load Balancing	BA	[218]
Mechanical Engineering	Manufacturing	BA, MOBA	[219–221]
	Structure Assessment	BA	[222, 223]
	Process Planning	BA, DIBA, HBA	[224–230]
Miscellaneous	Price/Effort Forecasting	BA	[231–233]
	E-Learning Content	BA	[234]
	Crowdsourcing	BA-ABC	[235]
	Observation Matrix Computation	BA	[236]
	Bloom Filter Optimization	BA	[237]
	Aircraft Landing Problem	BA	[238]
	Financial Trust Estimation	BA	[239]

Fig. 7 Distribution of BA in different application domains
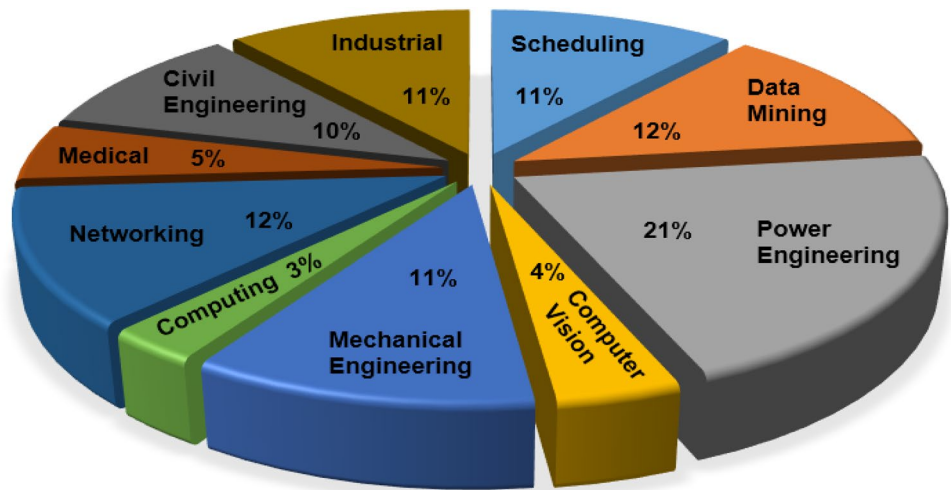
performance of BA and cuckoo search to optimize the bloom filter for spam word. Xie et al. [238] proposed a hybrid BA (HBA) to tackle the aircraft landing problem. Four different landing strategies were incorporated in the hybrid approach. HBA was evaluated on different instances of 500 aircrafts and found optimal solutions for most of the instances. Ochoa et al. [239] designed a support system for financial trust forest in Chihuahua. BA was used in the support system.

Table 4 depicts the summary of BA's applications in various domain. Figure 7 shows the distribution of BA's applications according to research papers included in this study.

6 Future Research Directions

It is observed from literature that researchers have tried to amend the structure of BA by hybridizing with other algorithms. Researchers and scientists have also modified the control parameters of BA to enhance their performance. Still, there are some open research areas in BA. The possible research directions are mentioned below:

6.1 Theoretical Investigation

It is observed from literature that the most of research papers related to BA were unable to provide theoretical foundation of BA and enhanced versions of BA. The authors have not provided any mathematical proof that how BA performs better than the existing metaheuristics and classical techniques. The mathematical analysis provides us the core concepts, which are responsible for superior performance. There is a need to analysis the structure, control parameters, and improvement theoretically.

6.2 Multi-population Optimization

The present research works reveal that the multi-population can be effortlessly added into other metaheuristic techniques. The multi-population metaheuristic algorithms performed better than the single-population metaheuristic algorithms in terms of diversity [240]. A miniature work has been done in the direction of multi-population BA. Hence, there is a lot of scope to develop effective multi-population BAs for various engineering problems.

6.3 Many-Objective Optimization

As per the knowledge of authors, there is only one many-objective BA is present in the literature. This variant utilized the dominance rank concept [119]. Hence, there is need to develop more specialized many-objective Bas, which can utilize the concepts of determinantal point processes, knee points, and hypervolume. Beside this, the reference points based dominance relation can also be integrated in BA to solve the many-objective problems.

6.4 Adaptive Module

Metaheuristic algorithms require an adaptive mechanism to solve the real-life problem in an effective manner. Some metaheuristic algorithm focus on intensification phase and trapped in local optima. Some metaheuristics emphasis diversification and require more resources to search the whole space. This mechanism can be helpful to maintain the balance between intensification and diversification [241, 242]. The adaptive module either selects the appropriate search operators or hyper-parameter tuning of control parameters during the BA's execution. Deep learning concepts such as Q-learning can be utilized to design the

adaptive module. Hence, the novel strategies are required to develop the adaptive mechanism for BA.

6.5 Hyper-heuristic Hybridization

BA has been hybridized with other metaheuristic algorithms to enhance their performance. The hybridization will help to diminish the weakness of BA [243]. However, this type of hybridization is known as low-level hybridization. The hybridization of BA with hyper-heuristic algorithms is known as high-level hybridization. In this hybridization, BA can choose the adaptive algorithm to perform the efficient search with penalties and rewards. Hence, there is a lot of scope to use hyper-heuristic algorithms with BA.

7 Conclusion

A systematic and updated review of BA is presented in this paper. The foremost intention of this paper is to recapitulate the various modifications in structure of BA and application domains. The research methodology for selecting the appropriate research papers has been discussed in detail. The fundamental concepts of BA has been studied with their control parameters. The different variants of BA such as binary, hybrid, levy flight, multi-objective and chaotic have been investigated with their pros and cons. The applicability of BA in different research areas has been discussed. The main emphasizes of the application domain are Power engineering and data mining. The possible research directions will motivate the researchers to study the BA and use it in real-life scenario.

This study not only provides the recent advancements in BA, but also discusses the control parameters used in these enhancements. This review will help the young scientists to understand the preliminary concepts of BA and utilize this information in their own research problems.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

1. Blum C, Roli A (2003) Metaheuristics in combinatorial optimization: overview and conceptual comparison. ACM Comput Surv 35(3):268–308
2. Velho L, Carvalho P, Gomes J, Figueiredo LD (2008) Mathematical optimization in computer graphics and vision. Elsevier, Amsterdam, Netherland
3. Mashwani WK, Haider R, Belhaouari SB (2021) A multi-swarm intelligence algorithm for expensive bound constrained optimization problems. Complexity 2021
4. Almufti SM, Marqas RB, Othman PS, Sallow AB (2021) Single-based and population-based metaheuristic for solving Np-hard problems. Iraqi J Sci 62(5):1–11
5. Kader MA, Zamil KZ, Ahmed BS (2021) A systematic review on emperor penguin optimizer. Neural Comput Appl
6. Mashwani WK, Shah H, Kaur M, Bakar MA, Miftahuddin M (2021) Large-scale bound constrained optimization based on hybrid teaching learning optimization algorithm. Alexand Eng J 60:6013–6033
7. Gharehchopogh FS, Gholizadeh H (2019) A comprehensive survey: whale optimization algorithm and its applications. Swarm Evolut Comput 48:1–24
8. Biswas A, Mishra KK, Tiwari S, Misra AK (2013). Physics-inspired optimization algorithms: a survey. J Optim 438152
9. Mashwani WK, Saha SNA, Belhaouari SB, Hamdi A (2021) Ameliorated ensemble strategy based evolutionary algorithm with dynamic resources allocations. Int J Comput Intell Syst 14(1):412–437
10. Shehab M, Abualigah L, Hamad HA, Alabool H, Alshinwan M, Khasawneh AM (2020) Moth–flame optimization algorithm: variants and applications. Neural Comput Appl 32:9859–9884
11. Dorigo M, Maniezzo V, Colorni A (1996) Ant system: optimization by a colony of cooperating agents. IEEE Trans Syst Man Cybern B 26(1):29–41
12. Kennedy J, Eberhart RC (1995) Particle swarm optimization. In: Proceedings of the IEEE international conference on neural networks, pp 1942–1948
13. Yang XS (2008) Nature-inspired meta-heuristic algorithms. Luniver Press, Moscow
14. Karaboga D (2005) An idea based on honeybee swarm for numerical optimization, technical report TR06. Erciyes University, Engineering Faculty, Computer Engineering Department
15. Geem ZW, Kim JH, Loganathan GV (2001) A new heuristic optimization algorithm: harmony search. SIMULATION 76:60–68
16. Yang XS, He XS (2013) Bat algorithm: literature review and applications. Int J Bio Inspired Comput 5:141–149
17. Chawla M, Duhan M (2015) Bat algorithm: a survey of the state-of-the-art. Appl Artif Intell 29(6):617–634
18. Kongkaew W (2017) Bat algorithm in discrete optimization: a review of recent applications. Songklanakarin J Sci Technol 39(5):641–650
19. Zebari AY, Almufti SM, Abdulrahman CM (2020) Bat algorithm (BA): review, applications and modifications. Int J Sci World 8(1):1–7
20. Gagnon I, April A, Abran A (2020) A critical analysis of the bat algorithm. Eng Rep 2, e12212
21. Umar SU, Rashid TA (2021) Critical analysis: bat algorithm-based investigation and application on several domains. World J Eng 18:4
22. Kaur A, Kumar Y (1950) (2021) Recent developments in bat algorithm: a mini review. Int J Phys Conf Ser 1:012055
23. Moher D, Liberati A, Tetzlaff J, Altman DG (2009) Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med 6(7):e1000097
24. Kumar V, Dogra N (2021) A comprehensive review on deep synergistic drug prediction techniques for cancer. Arch Comput Methods Eng 1–19
25. Kalra M, Tyagi S, Kumar V, Kaur M, Mashwani WK, Shah H, Shah K (2021) A comprehensive review on scatter search: techniques, applications, and challenges. Math Prob Eng 5588486:1–21
26. Yang X.S. (2010) A new metaheuristic bat-inspired algorithm. In: Gonzalez J.R., Pelta D.A., Cruz C., Terrazas G., Krasnogor

N. (eds) Nature inspired cooperative strategies for optimization (NICSO 2010). Studies in Computational Intelligence, vol 284. Springer, Berlin, Heidelberg

27. Metzner W (1991) Echolocation behaviour in bats. Sci Prog 1933:453–465
28. Richardson P (2008) Bats. Natural History Museum, London
29. Eberhart RC, Yuhui S, Kennedy J (2001) Swarm intelligence. Elsevier, Amsterdam
30. Chakri A, Khelif R, Benouaret M, Yang X-S (2017) New directional bat algorithm for continuous optimization problems. Exp Syst Appl 69:159–175
31. Chen YT, Shieh CS, Horng MF, Liao BY, Pan JS, Tsai MT (2014) A guidable bat algorithm based on doppler effect to improve solving efficiency for optimization problems. In: Hwang D, Jung J, Nguyen NT (eds) Computational collective intelligence. Technologies and applications, Vol. 8733. Springer, New York, pp 373–383
32. Meng X-B, Gao X, Liu Y, Zhang H (2015) A novel bat algorithm with habitat selection and Doppler effect in echoes for optimization. Exp Syst Appl 42:6350–6364
33. Wang X, Wang W, Wang Y (2013) An adaptive bat algorithm. In: Huang DS, Jo KH, Zhou YQ, Han K (eds) Intelligent computing theories and technology, Vol. 7996. Springer, Berlin Heidelberg, pp 216–223
34. Wang W, Wang Y, Wang X (2013) Bat algorithm with recollection. In: Huang DS, Jo KH, Zhou YQ, Han K (eds) Intelligent computing theories and technology, Vol. 7996. Springer, Berlin Heidelberg, pp 207–215
35. Li L, Zhou Y (2014) A novel complex-valued bat algorithm. Neural Comput Appl 25(6):1369–1381
36. Dao TK, Pan JS, Nguyen TT, Chu SC, Shieh CS (2014) Compact bat algorithm. In: Pan JS, Snasel V, Corchado ES, Abraham A, Wang SL (eds) Intelligent data analysis and its applications, volume II, vol 298. Springer, New York, pp 57–68
37. Ramli MR, Abas ZA, Desa MI, Abidin ZZ, Alazzam MB (2019) Enhanced convergence of Bat Algorithm based on dimensional and inertia weight factor. Comput Inform Sci 3(4):452–458
38. Fister I, Brest J, Yang XS (2015) Modified bat algorithm with quaternion representation. In: Proceedings of the 2015 IEEE congress on evolutionary computation, CEC 2015 (September), pp 491–498
39. Yilmaz S, Kucuksille EU, Cengiz Y (2014) Modified bat algorithm Elect Elect Eng 20(2):71–78
40. Alam MS, Kabir MWU (2014) Bat algorithm with self-adaptive mutation: A comparative study on numerical optimization problems. Int J Comput Appl 100(10):7–11
41. Yilmaz S, Kucuksille EU (2013) Improved bat algorithm for global optimization. Lect Notes Softw Eng 1(3):279–283
42. Jamil M, Zepernic H-J, Yang XS (2013) Improved bat algorithm for global optimization. Appl Soft Comput 48–75
43. Yilmaz S, Kucuksille EU (2014) A new modification approach on bat algorithm for solving optimization problems. Appl Soft Comput 28:259–275
44. Tsai PW, Pan JS, Liao BY, Tsai MJ, Istanda V (2012) Bat algorithm inspired algorithm for solving numerical optimization problems. Appl Mech Mater 148:134–137
45. Cai X, Gao XZ, Xue Y (2016) Improved bat algorithm with optimal forage strategy and random disturbance strategy. Int J Bio-Insp Comput 8:205
46. Zhu B, Zhu W, Liu Z, Duan Q, Cao L (2016) A novel quantum-behaved bat algorithm with mean best position directed for numerical optimization. Comput Intell Neurosci 2016:1–17
47. Rekaby A (2013) Directed artificial bat algorithm (DABA): a new bio-inspired algorithm. In: Proceedings of the 2013 international conference on advances in computing, communications and informatics (ICACCI), 2013. IEEE, pp 1241–1246
48. Kabir MWU, Sakib N, Chowdhury SMR, Alam MS (2014) A novel adaptive bat algorithm to control explorations and exploitations for continuous optimization problems. Int J Comput Appl 94:13
49. Topal AO, Altun O (2016) A novel meta-heuristic algorithm: dynamic virtual bats algorithm. Inf Sci 354:222–235
50. Cai X, Wang L, Kang Q, Qidi W (2014) Bat algorithm with gaussian walk. Int J Bio-Insp Comput 6(3):166–174
51. Zhou Y, Xie J, Li L, Ma M (2014) Cloud model bat algorithm. The Scientific World Journal, New York, pp 1–11
52. Cai X, Wang H, Cui Z, Cai J, Xue Y, Wang L (2017) Bat algorithm with triangle-flipping strategy for numerical optimization. Int J Mach Learn Cybern 9:199–215
53. Al-Betar MA, Awadallah MA (2018) Island bat algorithm for optimization. Exp Syst Appl 107:126–145
54. Gan C, Cao W, Wu M, Chen X (2018) A new bat algorithm based on iterative local search and stochastic inertia weight. Exp Syst Appl 104:202–212
55. Nawi NM, Rehman MZ, Khan A, Chiroma H, Herawan T (2016) A modified bat algorithm based on gaussian distribution for solving optimization problem J. Comput Theor Nanosci 13:706–714
56. Shan X, Cheng H (2017) Modified bat algorithm based on covariance adaptive evolution for global optimization problems. Soft Comput 22:5215–5230
57. Kiełkowicz K, Grela D (2016) Modified Bat algorithm for nonlinear optimization. Int J Comput Sci Netw Sec (IJCSNS) 16:46–50
58. Yahya NM, Tokhi MO (2017) A modified bats echolocation-based algorithm for solving constrained optimisation problems. Int J Bio-Insp Comput 10(1):12–23
59. Jaddi NS, Abdullah S, Hamdan AR (2015) Optimization of neural network model using modified bat-inspired algorithm. Appl Soft Comput 37:71–86
60. Ghanem W, Jantan A (2017) An enhanced bat algorithm with mutation operator for numerical optimization problems. Neural Comput Appl 31:1–35
61. Banati H, Chaudhary R (2017) Multi-modal bat algorithm with improved search (mmbais). J Comput Sci 23:130–144
62. Chaudhary R, Banati H (2019) Weighted multi-modal bat algorithm with improved search. Int J Hyb Intell 1(4):326–361
63. Chaudhary R, Banati H (2019) Swarm bat algorithm with improved search (SBAIS). Soft Comput 23:11461–11491
64. Banati H, Chaudhary R (2016) Enhanced shuffled bat algorithm (EShBAT). In: Proceedings of the 2016 international conference on advances in computing, communications and informatics (ICACCI), Jaipur, pp 731–738
65. Jaddi NS, Abdullah S, Hamdan AR (2015) Multi-population cooperative bat algorithm-based optimization of artificial neural network model. Elsevier, Amsterdam, Netherlands
66. Chaudhary R, Banati H (2017) Shuffled multi-population bat algorithm (SMPBat). In: Proceedings of the 2017 international conference on advances in computing, communications and informatics (ICACCI), Udupi, pp 541–547
67. Al-Betar MA, Awadallah MA, Faris H, Yang XS, Khader AT, Alomari OA (2018) Bat-inspired algorithms with natural selection mechanisms for global optimization. Neurocomputing 273:448–465
68. Cui Z, Li F, Zhang W (2019) Bat algorithm with principal component analysis. Int J Mach Learn Cybern 10(3):603–622
69. Wang Y, Wang P, Zhang J, Cui Z, Cai X, Zhang W, Chen J (2019) A novel bat algorithm with multiple strategies coupling for numerical optimization. Mathematics 7:135

70. Junaid M, Bangyal WH, Ahmed J (2020) A novel bat algorithm using sobol sequence for the initialization of population. Int Multitop Conf (INMIC).

71. Huang J, Ma Y (2020) Bat algorithm based on an integration strategy and Gaussian distribution. Math Prob Eng 2020:9495281

72. Bangyal WH, Ahmed J, Rauf HT (2020) A modified bat algorithm with torus walk for solving global optimisation problems. Int J Bio-insp Comput 15(1):1–13

73. Li C, Lian Z, Zhang T (2020) An optimized bat algorithm combining local search and global search. IOP Conf Ser Earth Environ Sci 571:012018

74. Alsalibi B, Abualigah L, Khader AT (2021) A novel bat algorithm with dynamic membrane structure for optimization problems. Appl Intell 51:1992–2017

75. Mashwani WK, Mehmood I, Bakar MA, Koccak I (2021) A modified bat algorithm for solving large-scale bound constrained global optimization problems. Math Prob Eng 2021:6636918

76. Mirjalili S, Mirjalili SM, Yang X-S (2013) Binary bat algorithm Neural Comput Appl 25(3–4):663–681

77. Rizk-Allah RM, Hassanien AE (2018) New binary bat algorithm for solving 0–1 knapsack problem. Comp Intell Syst 4:31–53

78. Sabba S, Chikhi S (2014) A discrete binary version of bat algorithm for multidimensional knapsack problem. Int J Bio-Insp Comput 6(2):140–152

79. Ma X-X, Wang J-S (2018) Optimized parameter settings of binary bat algorithm for solving function optimization problems. J Elect Comput Eng 2018

80. Dahi Z, Mezioud C, Draa A (2015) Binary bat algorithm: on the efficiency of mapping functions when handling binary problems using continuous-variable-based metaheuristics. In: International Conference on Computer Science and Its Applications (CIIA), May 2015, Saida, Algeria, pp 3–14

81. Tawhid MA, Dsouza KB (2018) Hybrid binary bat enhanced particle swarm optimization algorithm for solving feature selection problems. Appl Comput Inform 16(1/2):117–136

82. Meraihi Y, Acheli D, Ramdane-Cherif A (2016) An improved chaotic binary bat algorithm for QoS multicast routing. Int J Artif Intell Tools 25(4):1650025

83. Huang X, Zeng X, Han R (2017) Dynamic inertia weight binary bat algorithm with neighborhood search. Comput Intell Neurosci 2017:1–15

84. Ravindra M, Rao RS (2017) An upgraded binary bat algorithm approach for optimal allocation of PMUs in power system with complete observability. Int J Adv Appl Sci 4(10):33–39

85. Jordehi RA (2015) Chaotic bat swarm optimisation (CBSO). Appl Soft Comput 26:523–530

86. Lin J, Chou C, Yang C, Tsai H (2010) A chaotic levy flight bat algorithm for parameter estimation in nonlinear dynamic biological systems. J Comput Inf Technol 2(2):56–63

87. Gandomi AH, Yang X-S (2014) Chaotic bat algorithm J Comput Sci 5(2):224–232

88. Hamidzadeh J, Sadeghi R, Namaei N (2017) Weighted support vector data description based on chaotic bat algorithm. Appl Soft Comput 60:540–551

89. Xueting C, Ying L, Jiahao F (2020) Global chaotic bat optimization algorithm J. Northeast Univ (Nat Sci Edn) 41(4):488–491

90. Afrabandpey H, Ghaffari M, Mirzaei A, Safayani M (2014) A novel bat algorithm based on chaos for optimization tasks. In: Proceedings of intelligent systems (ICIS), Iranian Conference, pp 1–6.

91. Liu C, Chunming YE (2013) Bat algorithm with the characteristics of lévy flights. Caai Trans Intell Syst 8:240–246

92. Boudjemaa R, Ouaar F, Oliva D (2020) Fractional lévy flight bat algorithm for global optimization. Int J Bio-Insp Comput 15(2):100

93. Xie J, Zhou Y, Chen H (2013) A novel bat algorithm based on differential operator and Levy flights trajectory. Comput Intell Neurosci

94. Shan X, Liu K, Sun P-L (2016) Modified bat algorithm based on lévy flight and opposition based learning. Scientific Programming, 8031560

95. Jun L, Liheng L, Xianyi WA (2015) double-subpopulation variant of the bat algorithm. Appl Math Comput 263:361–377

96. Li Y, Li X, Liu J, Ruan X (2020) An improved bat algorithm based on lévy flights and adjustment factors. Symmetry 11(7):925

97. Fister IJ, Fister D, Yang X-S (2013) A hybrid bat algorithm ELEKTROTEHNISKIVESTNIK 80(1):1–7

98. Yildizdan G, Baykan OK (2020) A new hybrid BA_ABC algorithm for global optimization problems. Mathematics 8:1749

99. Wang G, Guo L (2013) A novel hybrid bat algorithm with harmony search for global numerical optimization. J Appl Math 2013:21

100. Ghanem WAHM, Jantan A (2011) Hybridizing bat algorithm with modified pitch-adjustment operator for numerical optimization problems. In: First EAI International Conference on Computer Science and Engineering.

101. Alihodzic A, Tuba M (2014) Improved hybridized bat algorithm for global numerical optimization. In: UKSim-AMSS 16th international conference on computer modelling and simulation, pp 57–62

102. Nguyen TT, Pan JS, Dao TK, Kuo MY, Horng MF (2014) Hybrid bat algorithm with artificial bee colony. In: Pan JS, Snasel V, Corchado, Abraham A, Wang SL (eds) Intelligent data analysis and its applications, Volume II, Vol. 298. Springer, New York, pp. 45–55

103. Rauf HT, Malik S, Shoaib U, Irfan MN, Lali MI (2020) Adaptive inertia weight Bat algorithm with Sugeno-Function fuzzy search. Appl Soft Comput 90:106159

104. Fister IJ, Fister D, Fister I (2013) Differential evolution strategies with random forest regression in the bat algorithm. In: Proceedings of the 15th annual conference companion on genetic and evolutionary computation, GECCO '13 Companion, 2013, pp. 1703–1706

105. Yildizdan G, Baykan ÖK (2020) A novel modified bat algorithm hybridizing by differential evolution algorithm. Exp Syst Appl 141:112949

106. He X-S, Ding W-J, Yang X-S (2014) Bat algorithm based on simulated annealing and Gaussian perturbations. Neural Comput Appl 25(2):459–468

107. Fister IJ, Fong S, Brest J, Fister I (2014) A novel hybrid self-adaptive bat algorithm. Sci World J, 709–738.

108. Pan TS, Dao TK, Nguyen TT, Chu SC (2015) Hybrid particle swarm optimization with bat algorithm. In: Sun H, Yang CY, Lin CW, Pan JS, Snasel V, Abraham A (eds) Genetic and evolutionary computing, vol. 329. Springer, New York, pp. 37–47

109. Liu Q, Wu L, Xiao W, Wang F, Zhang L (2018) A novel hybrid bat algorithm for solving continuous optimization problems. Appl Soft Comput 73:67–82

110. Guo L, Wang G-G, Wang H (2013) An novel hybrid bat algorithm with harmony search for global numerical optimization. Sci World J 2013:9

111. Meng X, Gao X, Liu Y (2015) A novel hybrid bat algorithm with differential evolution strategy for constrained optimization. Int J Hybrid Inform Technol 8(1):383–396

112. Pravesjit S (2016) A hybrid bat algorithm with natural-inspired algorithms for continuous optimization problem. Artif Life Robot 21(1):112–119

113. Yang X-S (2011) Bat algorithm for multi-objective optimisation. Int J Bio-Insp Comput 3(5):267–274

114. Yammani C, Maheswarapu S, Matam S (2016) A Multi-objective Shuffled Bat algorithm for optimal placement and sizing of multi distributed generations with different load models. Int J Elect Power Energy Syst 79:120131

115. Prakash S, Trivedi V, Ramteke M (2016) An elitist non-dominated sorting bat algorithm NSBAT-II for multi-objective optimization of phthalic anhydride reactor. Int J Syst Assur Eng 7(3):299–315

116. Heraguemi KE, Kamel N, Drias H (2018) Multi-objective bat algorithm for mining numerical association rules. Int J Bio-Insp Comput 11:4

117. Laudis LL, Shyam S, Jemila C, Suresh V (2018) MOBA: multi objective bat algorithm for combinatorial optimization in VLSI. Proced Comput Sci 125:840–846

118. Chen G, Qian J, Zhang Z, Sun Z (2019) Multi-objective improved bat algorithm for optimizing fuel cost, emission and active power loss in power system. Int J Comput Sci 46:1

119. Perwaiz U, Younas I, Anwar AA (2020) Many-objective BAT algorithm. PLoS ONE 15(6):e0234625

120. Han Y, Qian J, Chen G (2021) Research of multi-objective modified bat algorithm on optimal power flow problems. Int J Syst Control Inform Process 3(2):150–171

121. Sheah RH, Abbas IT (2021) Using multi-objective bat algorithm for solving multi-objective non-linear programming problem. Iraqi J Sci 62(3):997–1015

122. Jiang M, Liu W, Xu W, Chen W (2021) Improved multiobjective bat algorithm for the credibilistic multiperiod mean-VaR portfolio optimization problem. Soft Comput 8

123. Ahmadianfar I, Adib A, Salarijazi M (2016) Optimizing multireservoir operation: hybrid of bat algorithm and differential evolution. J Water Resourc Plan Manag 142(2):05015010

124. Ethteram M, Mousavi S-F, Farzin S, Deo R, Othman FB, Chau K-W, Sarkamaryan S, Singh VP, El-Shafie A (2018) Bat algorithm for dam-reservoir operation. Environ Earth Sci 77(13):1–15

125. Bozorg-Haddad O, Karimirad I, Seifollahi-Aghmiuni S, Loáiciga HA (2014) Development and application of the bat algorithm for optimizing the operation of reservoir systems. J Water Resour Plan Manag 141:04014097

126. Bath GS, Dhillon JS, Walia BS (2021) Blended bat algorithm for optimum design of cantilever retaining wall. Levant J 20(8):175–196

127. Bath GS, Dhillon JS, Walia BS (2020) Geometric design of retaining wall by bat algorithm. Sci Eng J 24(12):1–20

128. Farzin S, Karami H, Anaraki MV, Ehteram M (2018) The application of bat algorithm for economical design of open channels. Iran J Irrig Drain 12(3):635–646

129. Talatahari S, Kaveh A (2015) Improved bat algorithm for optimum design of large-scale truss structures. Int J Optim Civil Eng 5(2):241–254

130. Yancang L, Zhen Y (2019) Application of improved bat algorithm in truss optimization. KSCE J Civil Eng 23:2636–2643

131. Kaveh A, Zakian P (2014) Enhanced bat algorithm for optimal design of skeletal structures. Asian J Civil Eng 15:179–212

132. Aalimahmoody N, Bedon C, Hasanzadeh-Inanlou N, Hasanzade-Inallu A, Nikoo M (2021) BAT algorithm-based ANN to predict the compressive strength of concrete: a comparative study. Infrastructures 6:80

133. Su Y, Liu L, Lei Y (2021) Structural damage identification using a modified directional bat algorithm. Appl Sci 11:6507

134. Nakamura RYM, Pereira LAM, Costa KA, Rodrigues D, Papa JP, Yang XS (2012) BBA: a binary bat algorithm for feature selection. In: Proceedings of the 2012 25th SIBGRAPI conference on graphics, patterns and images (SIBGRAPI), 2012, pp. 291–297.

135. Taha AM, Mustapha A, Chen SD (2013) Naive bayes-guided bat algorithm for feature selection. Sci World J

136. Rodrigues D, Pereira LA, Nakamura RY, Costa KA, Yang X-S, Souza AN, Papa JP (2014) A wrapper approach for feature selection based on bat algorithm and optimum-path forest. Exp Syst Appl 41(5):2250–2258

137. Alihodzic A, Tuba E, Simian D, Tuba V, Tuba M (2018) Extreme learning machines for data classification by improved bat algorithm. International Joint Conference on Neural Networks, Brazil.

138. Leke CA, Marwala T (2019) Missing data estimation using bat algorithm. Deep learning and missing data in engineering systems, Springer, Berlin, Germany.

139. Talal R (2014) Comparative study between the (BA) algorithm and (PSO) algorithm to train (RBF) network at data classification 92 (5), 16–22

140. Cheruku R, Edla DR, Kuppili V, Dharavath R (2017) RST-Bat-Miner: a fuzzy rule miner integrating rough set feature selection and bat optimization for detection of diabetes disease. Appl Soft Comput 67:764–780

141. Taha AM, Tang AY (2013) Bat algorithm for rough set attribute reduction. J Theor Appl Inform Technol 51(1):1–8

142. Banu AF, Chandrasekar C (2013) An optimized approach of modified BAT algorithm to record deduplication. Int J Comput Appl 62(1):10–15

143. Komarasamy G, Wahi A (2012) An optimized k-means clustering technique using bat algorithm. Eur J Sci Res 84(2):263–273

144. Sood M, Bansal S (2013) K-medoids clustering technique using bat algorithm. Int J Appl Inform Syst 5(8):20–22

145. Aboubi Y, Drias H, Kamel N (2016) BAT-CLARA: BAT-inspired algorithm for Clustering LARge Applications. IFAC-PapersOnLine 49(2):243–248

146. Heraguemi KE, Kamel N, Drias H (2016) Multi-swarm bat algorithm for association rule mining using multiple cooperative strategies. Appl Intell 45:1021–1033

147. Zhang JW, Wang GG (2012) Image matching using a bat algorithm with mutation. Appl Mech Mater 203:88–93

148. Alihodzic A, Tuba M (2014) Improved bat algorithm applied to multilevel image thresholding. Sci World J 2014

149. Alsalibi B, Venkat I, Al-Betar MA (2017) A membrane-inspired bat algorithm to recognize faces in unconstrained scenarios. Eng Appl Artif Intell 64:242–260

150. Akhtar S, Ahmad AR, Abdel-Rahman EM (2012) A metaheuristic bat-inspired algorithm for full body human pose estimation. In: Proceedings of the 2012 ninth conference on computer and robot vision (CRV), 2012, pp. 369–375

151. Alomari OA, Khader AT, Al-Betar MA, Abualigah LM (2017) MRMR BA: a hybrid gene selection algorithm for cancer classification. J Theor Appl Inf Technol 95(12):2610–2618

152. Mishra S, Shaw K, Mishra D (2012) A new meta-heuristic bat inspired classification approach for microarray data. Proced Technol 4:802–806

153. Lu S, Qiu X, Shi J, Li N, Lu Z-H, Chen P, Yang M-M, Liu F-Y, Jia W-J, Zhang Y (2017) A pathological brain detection system based on extreme learning machine optimized by bat algorithm. CNS Neurol Disord Drug Targets (Form Curr Drug Targ CNS Neurol Disord) 16(1):23–29

154. Lu S, Wang S-H, Zhang Y-ZD (2021) Detection of abnormal brain in MRI via improved AlexNet and ELM optimized by chaotic bat algorithm. Neural Comput Appl 33:10799–10811

155. Kora P, Kalva SR (2015) Improved Bat algorithm for the detection of myocardial infarction. Springerplus 4(1):666

156. Marichelvam M, Prabaharan T, Xin-She Y, Geetha M (2013) Solving hybrid flow shop scheduling problems using bat algorithm. Int J Log Econ Global 5(1):15–29

157. Luo Q, Zhou Y, Xie J, Ma M, Li L (2014) Discrete bat algorithm for optimal problem of permutation flow shop scheduling. Sci World J 2014.

158. Tosun Ö, Marichelvam MK (2016) Hybrid bat algorithm for flow shop scheduling problems. Int J Math Oper Res 9(1):125–138

159. Marichelvam M, Prabaharam T (2012) A bat algorithm for realistic hybrid flowshop scheduling problems to minimize makespan and mean flow time. ICTACT J Soft Comput 3(1):428–433

160. Xie J, Zhou Y, Tang Z (2013) Differential Lévy-Flights bat algorithm for minimization makespan in permutation flow shops. In: Huang DS, Jo KH, Zhou YQ, Han K (eds) Lecture notes in computer science, vol 7996. Intelligent computing theories and technology. Springer, Berlin, pp 179–188

161. Dao TK, Pan TS, Nguyen TT, Pan JS (2015) Parallel bat algorithm for optimizing makespan in job shop scheduling problems J. Intell Manuf 29:1–12

162. Musikapun P, Pongcharoen P (2012) Solving multi-stage multi-machine multi-product scheduling problem using bat algorithm. Int Proc Econ Develop Res 35:98–102

163. Malakooti B, Kim H, Sheikh S (2012) Bat intelligence search with application to multi-objective multi-processor scheduling optimization. Int J Adv Manuf Technol 60(9–12):1071–1086

164. Talafuse TP, Pohl EA (2016) A bat algorithm for the redundancy allocation problem. Eng Optim 48(5):900–910

165. Fister I, Rauter S, Yang X-S, Ljubic K (2014) Planning the sports training sessions with the bat algorithm. Neurocomputing 149:993–1002

166. Khan K, Nikov A, Sahai A (2011) A fuzzy bat clustering method for ergonomic screening of office workplaces. In: Dicheva D, Markov Z, Stefanova E (eds) Third international conference on software, services and semantic technologies, number 101 in advances in intelligent and soft computing. Springer, Berlin Heidelberg, pp 59–66

167. Osaba E, Yang X-S, Diaz F, Lopez-Garcia P, Carballedo R (2016) An improved discrete bat algorithm for symmetric and asymmetric traveling salesman problems. Eng Appl Artif Intell 48:59–71

168. Saji Y, Riffi ME (2016) A novel discrete bat algorithm for solving the travelling salesman problem. Neural Comput Appl 27(7):1853–1866

169. Bora TC, Coelho LDS, Lebensztajn L (2012) Bat-inspired optimization approach for the brushless DC wheel motor problem. IEEE Trans Magn 48(2):947–950

170. Ali ES (2014) Optimization of power system stabilizers using BAT search algorithm. Int J Electr Power Energy Syst 61(2014):683–690

171. Peres W, de Oliveira EJ, Filho JAP, Silva ICD (2015) Coordinated tuning of power system stabilizers using bio-inspired algorithms. Int J Elect Power Energy Syst 64:419–428

172. Sambariya DK, Prasad R (2014) Robust tuning of power system stabilizer for small signal stability enhancement using metaheuristic bat algorithm. Int J Electr Power Energy Syst 61:229–238

173. Sathya MR, Ansari MMT (2015) Load frequency control using Bat inspired algorithm based dual mode gain scheduling of PI controllers for interconnected power system. Int J Electr Power Energy Syst 64:365–374

174. Sathya MR, Ansari MMT (2014) Design of BAT inspired algorithm based dual mode gain scheduling of PI load frequency control controllers for interconnected multi-area multi-unit power systems. Aust J Basic Appl Sci 8(18):635–647

175. Sakthivel S, Natarajan R, Gurusamy P (2013) Application of bat optimization algorithm for economic load dispatch considering valve point effects. Int J Comput Appl 67(11):35–39

176. Bestha M, Reddy KH, Hemakeshavulu O (2014) Economic load dispatch downside with valve point result employing a binary bat formula. Int J Elect Comput Eng (IJECE) 4(1):101–107

177. Biswal S, Barisal A, Behera A, Prakash T (2013) Optimal power dispatch using bat algorithm. In: International conference on energy efficient technologies for sustainability (ICEETS), 1018–1023.

178. Ramesh B, Mohan VCJ, Ressy VCV (2013) Application of bat algorithm for combined economic load and emission dispatch. J Electr Eng Telecommun 2(1):1–9

179. Niknam T, Azizipanah-Abarghooee R, Zare M, Bahmani-Firouzi B (2013) Reserve constrained dynamic environmental/economic dispatch: a new multiobjective self-adaptive learning bat algorithm. IEEE Syst J 7(4):763–776

180. Latif A, Palensky P Economic dispatch using modified bat algorithm. Algorithms 7(3): 328–338

181. Bahmani-Firouzi B, Azizipanah-Abarghooee R (2014) Optimal sizing of battery energy storage for micro-grid operation management using a new improved bat algorithm. Int J Electr Power Energy Syst 56(2014):42–54

182. Eltamaly AM, Al-Saud MS, Abokhalil AG (2020) A novel scanning bat algorithm strategy for maximum power point tracker of partially shaded photovoltaic energy systems. Ain Shams Eng J 11(4):1093–1103

183. Seyedmahmoudian M et al (2018) Maximum power point tracking for photovoltaic systems under partial shading conditions using bat algorithm. Sustainability 10(5):1347

184. Eltamaly AM, Al-Saud MS, Abokhalil AG (2020) A novel bat algorithm strategy for maximum power point tracker of photovoltaic energy systems under dynamic partial shading. IEEE Access 8:10048–10060

185. Kaced K et al (2017) Bat algorithm based maximum power point tracking for photovoltaic system under partial shading conditions. Sol Energy 158:490–503

186. Niknam T, Sharifinia S, Azizipanah-Abarghooee R (2013) A new enhanced bat-inspired algorithm for finding linear supply function equilibrium of GENCOs in the competitive electricity market. Energy Convers Manag 76:1015–1028

187. Tamiru AL, Hashim FM (2013) Application of bat algorithm and fuzzy systems to model exergy changes in a gas turbine. In: Artificial intelligence, evolutionary computing and metaheuristics. Springer, Berlin, Germany

188. Kotteeswaran R, Sivakumar L (2013) A novel bat algorithm based re- tuning of PI controller of coal gasifier for optimum response. In: Prasath R, Kathirvalavakumar T (eds) Mining intelligence and knowledge exploration, number 8284 in lecture notes in computer science. Springer, New York, pp 506–517

189. Tamiru AL, Hashim FM (2011) Use of fuzzy systems and bat algorithm for exergy modelling in a gas turbine generator. In: Proceedings of the 2011 IEEE colloquium on humanities, science and engineering (CHUSER), pp 305–310

190. Kashi S, Minuchehr A, Poursalehi N, Zolfaghari A (2014) Bat algorithm for the fuel arrangement optimization of reactor core. Ann Nucl Energy 64:144–151

191. Zhou Y, Xie J, Zheng H (2013) A hybrid bat algorithm with path relinking for capacitated vehicle routing problem. Math Prob Eng 2013:1–10

192. Zhou Y, Luo Q, Xie J, Zheng H (2016) A hybrid bat algorithm with path relinking for the capacitated vehicle routing problem. In: Yang XS, Bekdaş G, Nigdeli SM (eds) Modeling and optimization in science and technologies, vol 7. Metaheuristics and optimization in civil engineering. Springer, Cham, pp 255–276

193. Ochoa A, Margain L, Arreola J, Luna AD, García G, Soto E, González S, Haltaufoerhyde K, Scarandangotti V (2013) Improved solution based on bat algorithm to vehicle routing problem in a caravan range community. In: Proceedings of the 2013 13th international conference on hybrid intelligent systems (HIS), pp 18–22

194. Taha A, Hachimi M, Moudden A (2015) Adapted bat algorithm for capacitated vehicle routing problem. Int Rev Comput Softw 10(6):610–619

195. Dapa K, Loreungthup P, Vitayasak S, Pongcharoen P (2013) Bat algorithm, genetic algorithm and shuffled frog leaping algorithm for designing machine layout. In: Romanna S, Lingras P, Sombattheera C, Krishna A (eds) Lecture notes in computer science, vol 8271. Multi-disciplinary trends in artificial intelligence. Springer, Berlin, pp 59–68

196. He M, Sun L, Zeng X, Liu W, Tao S (2020) Node layout plans for urban underground logistics systems based on heuristic Bat algorithm. Comput Commun 154:465–480

197. Büyüksaatç S (2015) Bat algorithm application for the single row facility layout problem. In: Yang XS (ed) Studies in computational intelligence, vol 585. Recent advances in swarm intelligence and evolutionary computation. Springer, Cham, pp 101–120

198. Carbas S, Hasancebi O (2013) Optimum design of steel space frames via bat inspired algorithm. In: Proceedings of the 10th world congress on structural and multidisciplinary optimization

199. Hasançebi O, Carbas S (2014) Bat inspired algorithm for discrete size optimization of steel frames. Adv Eng Softw 67:173–185

200. Gholizadeh S, Shahrezaei AM (2015) Optimal placement of steel plate shear walls for steel frames by bat algorithm. Struct Des Tall Spec Build 24(1):1–18

201. Hasancebi O, Teke T, Pekcan O (2013) A bat-inspired algorithm for structural optimization. Comput Struct 128:77–90

202. Arora U, Lodhi EA, Saxena T (2016) PID parameter tuning using modified bat algorithm J. Autom Control Eng 4:347–352

203. Omar B, Saida IB (2014) Bat algorithm for optimal tuning of PID controller in an AVR system. In: International conference on control, engineering and information, pp 158–170

204. Sur C, Shukla A (2013) Adaptive and discrete real bat algorithms for route search optimization of graph based road network. In: Proceedings of the 2013 international conference on machine intelligence and research advancement (ICMIRA), pp 120–124

205. Xi Z, Wang J, Yang Q, Li X, Zheng J, Yan W (2018) Optimal path planning for UAVs based on an improved bat algorithm. In: Proceedings of international multi-conference on complexity, informatics and cybernetics, pp. 40–45

206. Wang G, Guo L, Duan H, Liu L, Wang H (2012) A bat algorithm with mutation for UCAV path planning. Sci World J 2012:1–15

207. Li YG, Peng JP (2014) An improved bat algorithm and its application in multiple ucavs. Appl Mech Mater 442:282–286

208. Kiran M, Reddy GRM (2014) Bat-termite: a novel hybrid bio inspired routing protocol for mobile ad hoc networks. Int J Wireless Mob Comput 7(3):258–269

209. Pal S, Sethi S (2016) BAT-based optimized routing protocol in cognitive radio ad hoc network. Int J Appl Innov Eng Manag (IJAIEM) 4(12):116–123

210. Parika W, Seesuaysom W, Vitayasak S, Pongcharoen P (2013) Bat algorithm for designing cell formation with a consideration of routing flexibility. In: Proceedings of the 2013 IEEE international conference on industrial engineering and engineering management (IEEM), 1353–1357

211. Goyal S, Patterh MS (2016) Modified bat algorithm for localization of wireless sensor network. Wireless Pers Commun 86(2):657–670

212. Kaur SP, Sharma M (2015) Radially optimized zone-divided energy-aware wireless sensor networks (WSN) protocol using BA (Bat Algorithm). IETE J Res 61(2):170–179

213. Cao Y, Cui Z, Li F, Dai C, Chen W (2014) Improved low energy adaptive clustering hierarchy protocol based on local centroid bat algorithm. Sens Lett 12:1372–1377

214. Lin CC, Li YS, Deng DJ (2014). A bat-inspired algorithm for router node placement with weighted clients in wireless mesh networks. In: Proceedings of the 2014 9th international conference on communications and networking in China (CHINACOM), pp 139–143

215. Hassan EA, Hafez AI, Hassanien AE, Fahmy AA (2015) A discrete bat algorithm for the community detection problem. International conference on hybrid artificial intelligence systems. Springer, New York, pp 188–199

216. Imane M, Nadjet K (2016) Hybrid Bat algorithm for overlapping community detection. IFAC-PapersOnLine 49:1454–1459

217. Raghavan S, Sarwesh P, Marimuthu C, Chandrasekaran K (2015) Bat algorithm for scheduling workflow applications in cloud. In: Proceedings of the 2015 international conference on electronic design, computer networks automated verification (EDCAV), pp 139–144

218. Sharma S, Luhach AK, Abdhullah SS (2016) An optimal load balancing technique for cloud computing environment using bat algorithm. Indian J Sci Technol 9(28):1–4

219. Suárez P, Iglesias A, Gálvez A (2019) Make robots be bats: specializing robotic swarms to the bat algorithm. Swarm Evolut Comput 44:113–129

220. Mallick R, Ganguli R (2018) Robust design of helicopter rotor flaps using bat algorithm. In: Handbook research on predictive modeling and optimization methods in science and engineering. pp 1–28

221. Kumaravel G, Kumar C (2012) Design of self-tuning PI controller for STATCOM using Bats echolocation algorithm based neural controller. In: IEEE-international conference on advances in engineering, science and management (ICAESM-2012), pp 276–281

222. Bekdas G, Nigdeli SM, Yang XS (2018) A novel bat algorithm based optimum tuning of mass dampers for improving the seismic safety of structures. Eng Struct 159:89–98

223. Chakri A, Khelif R, Benouaret M (2016) Improved bat algorithm for structural reliability assessment: application and challenges. Multidiscip Model Mater Struct 12(2):218–253

224. Wang J, Fan X, Zhao A, Yang M (2015) A hybrid bat algorithm for process planning problem. IFAC-PapersOnLine 48(3):1708–1713

225. Naderi M, Khamehchi E (2017) Application of DOE and metaheuristic bat algorithm for well placement and individual well controls optimization. J Nat Gas Sci Eng

226. Osaba E, Yang XS, Fister I, Del Ser J, Lopez-Garcia P, Vazquez-Pardavila AJ (2018) A discrete and improved bat algorithm for solving a medical goods distribution problem with pharmacological waste collection. Swarm Evolut Comput

227. Delalic S, Alihodzic A, Tuba M, Selmanovic E, Hasic D (2020) Discrete bat algorithm for event planning optimization. In: International convention on information, communication and electronic technology (MIPRO)

228. Liu Q, Li J, Wu L, Wang F, Xiao W (2020) A novel bat algorithm with double mutation operators and its application to low-velocity impact localization problem. Eng Appl Artif Intel 90:103505

229. Kongkaew W (2015) Solving the single machine total weighted tardiness problem using bat-inspired algorithm. In: Proceedings of the 2015 IEEE international conference on industrial engineering and engineering management (IEEM), pp 265–269.

230. Sadeghi J, Mousavi SM, Niaki STA, Sadeghi S (2014) Optimizing a bi-objective inventory model of a three-echelon supply chain using a tuned hybrid bat algorithm. Transp Res E Log Transp Rev 70:274–292

231. Dehghani H, Bogdanovic D (2018) Copper price estimation using bat algorithm. Resour Policy 55:55–61

232. Srivastava PR, Bidwai A, Khan A, Rathore K, Sharma R, Yang XS (2014) An empirical study of test effort estimation based on bat algorithm. Int J Bio-Insp Comput 6(1):57–70

233. Hong W, Li M, Geng J, Zhang Y (2019) Novel chaotic bat algorithm for forecasting complex motion of floating platforms. Appl Math Model 72:425–443

234. Koffka A, Sahai K (2012) A comparison of BA, GA, PSO, BP and LM for training feed forward neural networks in e-learning context. IJ Intell Syst Appl 4(7):23–29

235. Cincy W, Jeba J (2017) Performance analysis of novel hybrid A-BAT algorithm in crowdsourcing environment. Int J Appl Eng Res 12:14964–21496

236. Cui Z, Zhang C, Zhao Y, Shi Z (2019) Adaptive bat algorithm optimization strategy for observation matrix. Appl Sci 9:3008

237. Natarajan A, Subramanian S, Premalatha K (2012) A comparative study of cuckoo search and bat algorithm for Bloom filter optimisation in spam filtering. Int J Bio-Insp Comput 4(2):89–99

238. Xie J, Zhou Y, Zheng H (2013) A hybrid metaheuristic for multiple runways aircraft landing problem based on bat algorithm. J Appl Math

239. Ochoa A, Margain L, Hernandez A, Ponce J, De Luna A, Hernandez A, Castillo O (2013) Bat algorithm to improve a financial trust forest. In: Proceedings of the 2013 world congress on nature and biologically inspired computing (NaBIC), pp 58–62. IEEE

240. Ma H, Shen S, Yu M, Yang Z, Fei M, Zhou H (2019) Multi-population techniques in nature inspired optimization algorithms: a comprehensive survey. Swarm Evol Comput 44:365–387

241. Zamli KZ, Din F, Baharom S, Ahmed BS (2017) Fuzzy adaptive teaching learning-based optimization strategy for the problem of generating mixed strength t-way test suites. Eng Appl Artif Intell 59:35–50

242. Cheng M-Y, Prayogo D (2018) Fuzzy adaptive teaching–learning-based optimization for global numerical optimization. Neural Comput Appl 29(2):309–327

243. Ting TO, Yang XS, Cheng S, Huang K (2015) Hybrid metaheuristic algorithms: past, present, and future. In: Yang X-S (ed) Recent advances in swarm intelligence and evolutionary computation. Springer, Cham, pp 71–83