A Comprehensive Review of the Fireworks Algorithm

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The fireworks algorithm, which is inspired from the phenomenon of fireworks explosion, is a special kind of swarm intelligence algorithm proposed in 2010. Since then, it has been attracting more and more research interest and has been widely employed in many real-world problems due to its unique search manner and high efficiency. In this article, we present a comprehensive review of its advances and applications. We begin with an introduction to the original fireworks algorithm. Then we review its algorithmic research work for single objective and multi-objective optimization problems. After that, we present the theoretical analyses of the fireworks algorithm. Finally, we give a brief overview of its applications and implementations. Hopefully, this article could provide a useful road map for researchers and practitioners who are interested in this algorithm and inspire new ideas for its further development.

CCS Concepts: • **Theory of computation → Evolutionary algorithms**; **Bio-inspired optimization**;

Additional Key Words and Phrases: Fireworks algorithm, evolutionary computation, swarm intelligence

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1 INTRODUCTION

Optimization is one of the most fundamental and common problems in science and industry. Convex optimization with available derivatives can be solved efficiently by gradient-based algorithms like gradient descent or the Newton's method. However, there is no derivative information in black-box or discrete optimization problems, and gradient-based algorithms are often trapped in local optima when optimizing multi-modal objective functions even though there is derivative information. Therefore, a new branch of approaches, i.e., evolutionary computation was proposed and developed, which do not require derivative information and can keep a balance between exploitation and exploration in the global search process. Nowadays, evolutionary computation has become one of the most active subfield of artificial intelligence.

Evolutionary computation in a narrow sense refer to algorithms that are directly inspired by biological evolutionary phenomena, such as evolutionary strategy and the genetic algorithm. While evolutionary computation in a broad sense refer to all derivative-free iterative optimization algorithms, including metaphor-based algorithms (meta-heuristics) and direct methods such as the downhill simplex method and estimation of distribution algorithms. So far, more than one hundred

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different evolutionary algorithms have been proposed to solve different kinds of optimization problems [200].

Swarm intelligence algorithms (e.g., particle swarm optimization (PSO) [81], artificial bee colony (ABC) [78], and ant colony optimization (ACO) [44]) are a special group of evolutionary algorithms that are featured by various effective cooperative mechanisms among individuals within the population. However, evolutionary algorithms in a narrow sense (e.g., genetic algorithm (GA) [55] and evolution strategy (ES) [127]) accomplish global optimization by competitive mechanisms inspired by the natural selection process. To combine the advantages of both branches, the fireworks algorithm has been proposed. The fireworks algorithm employs a unique framework allowing both cooperative and competitive mechanisms and a novel search manner called explosion. It has been attracting more and more research interest due to its unique design and high efficiency. In this article, we present a comprehensive review of the fireworks algorithm for its researchers and practitioners.

2 FIREWORKS ALGORITHM

The fireworks algorithm (FWA) is a new kind of global optimization algorithm proposed by Tan and Zhu [172] in 2010. It conducts the global search by mimicking the phenomenon of fireworks explosion. The algorithm is featured by (1) an explosive search manner and (2) a framework enabling multiple (sub)populations to interact. Since it was proposed, the FWA has attracted much research interest and has been widely applied in real-world optimization problems. In this article, the fireworks algorithm proposed in 2010 is referred to as "the original fireworks algorithm."

Without loss of generality, the following continuous minimization problem is considered in this section:

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}), \tag{1}$$

where $\mathbf{x}$ represents a vector in the d-dimensional Euclidean space. The purpose of the algorithm is to locate the optimal $\mathbf{x}^*$, which means it is of the minimal evaluation/fitness value $f(\mathbf{x}^*)$.

2.1 Framework

The original FWA repeats the following steps until the terminal criterion (required precision, maximal function evaluations, etc.) is met. (1) At the beginning, randomly choose some locations in the search space as the initial locations of the fireworks. (2) Conduct explosive search around the locations of the fireworks to generate explosion sparks. (3) Mutate the fireworks by certain rules to generate mutation sparks. (4) Select the fireworks of the next generation from the current fireworks and sparks.

Many improvements have been made upon the operators in the FWA, yet most variants generally follow the framework introduced above. Therefore, this can be considered as the basic framework of the FWA.

There are four main operators in the original fireworks algorithm: the explosion operator, the mutation operator, the selection operator and the mapping rule.

2.2 Explosion

The fireworks algorithm is inspired by the phenomenon of fireworks explosion. Although there are essential differences between the algorithm and the real fireworks, the metaphor captures the core feature of the explosive search manner of the algorithm. The explosion operator is the basic search manner in the FWA. In the explosion operator, a certain number of explosion sparks are generated within a certain explosion amplitude around each firework. In the original FWA, if the fitness of a firework is relatively good, then more explosion sparks will be generated within a smaller explosion amplitude around it to conduct local exploitation. While, if the fitness of a firework is relatively bad, then fewer explosion sparks will be generated within a larger explosion amplitude around it to conduct global exploration. The fireworks interchange the information of fitness values to determine the allocation of explosion sparks' numbers and explosion amplitudes.

In the original FWA, the number of explosion sparks of each firework is determined by the following equation:

$$\lambda_i = \lambda \cdot \frac{\max_k(f(\mathbf{X}_k)) - f(\mathbf{X}_i)}{\sum_j (\max_k(f(\mathbf{X}_k)) - f(\mathbf{X}_j))}, \tag{2}$$

where $\mathbf{X}_i$ is the location of the ith firework. Obviously, $\lambda = \sum_i \lambda_i$. Therefore, λ is a parameter to control the total number of explosion sparks in each generation. The smaller $f(\mathbf{X}_i)$ is, the more explosion sparks are generated. To avoid the overwhelming effect of good fireworks, thresholds are set in the original FWA:

$$\lambda_i = \begin{cases} \text{round}(a\lambda) & \text{if } \lambda_i < a\lambda \\ \text{round}(b\lambda) & \text{if } \lambda_i > b\lambda \\ \text{round}(\lambda_i) & \text{otherwise} \end{cases}, \tag{3}$$

where round(x) means the integer closest to x, a and b ($a < b < 1$) are two parameters to control the lower and upper boundaries of explosion sparks' number.

The explosion amplitude of each firework is determined by the following equation:

$$A_i = A \cdot \frac{f(\mathbf{X}_i) - \min_k(f(\mathbf{X}_k))}{\sum_j (f(\mathbf{X}_j) - \min_k(f(\mathbf{X}_k)))}. \tag{4}$$

Likewise, A is a parameter to control the total explosion amplitude. The smaller $f(\mathbf{X}_i)$, the smaller the amplitude.

Algorithm 1 shows how the explosion sparks of the ith firework are generated, where d is the dimensionality of the search space and s_{ijk} is the kth dimension of the jth explosion spark of the ith firework.

2.3 Mutation

Aside from explosion sparks, a number of mutation sparks are also generated in the original FWA by the mutation operator, as shown in Algorithm 2, where $\dot{\lambda}$ is the number of mutation sparks.

2.4 Mapping Rule

Real-world optimization problems and standard benchmark suites are often with boundary constraints $\mathbf{x} \in [\mathbf{lb}, \mathbf{ub}]$, which is a simple kind of constraint compared with other equality or inequality constraints. In the FWA, newly generated explosion or mutation sparks may be located outside the boundaries, in which case they need to be replaced by ones within the boundaries, otherwise function evaluations may be wasted.

ALGORITHM 1: Explosion Operator

```
for j = 1 to λ_i do
    e ← A_i · rand(−1, 1)
    randomly choose z dimensions, z ← round(d · rand(0, 1))
    s_ij ← X_i
    for each chosen dimension k do
        s_ijk ← s_ijk + e
    end
end
```

ALGORITHM 2: Mutation Operator

for $j = 1$ **to** λ **do**
  randomly choose a firework $\mathbf{X}_i$
  $e \leftarrow \text{randn}(1, 1)$
  randomly choose z dimensions, $z \leftarrow \text{round}(d \cdot \text{rand}(0, 1))$
  $\text{G}_j \leftarrow \mathbf{X}_i$
  for *each chosen dimension k* **do**
    $G_{jk} \leftarrow G_{jk} \cdot e$
  end
end

In the original FWA, a modular arithmetic-based mapping rule is used. If an individual $\mathbf{x}$ satisfies $x_k < \text{lb}_k$ or $x_k > \text{ub}_k$ in dimension k, then

$$x_k \leftarrow \text{lb}_k + |x_k| \bmod (\text{ub}_k - \text{lb}_k). \tag{5}$$

2.5 Selection

In every generation, after the sparks are generated, it is necessary to select the fireworks of the next generation. In the original FWA, a density-based selection mechanism is proposed, intending to maintain the representativeness and the diversity of selected fireworks.

First, the candidate (including current fireworks and sparks) of the best fitness value is selected as a firework.

Second, the rest $\mu - 1$ fireworks are selected from the rest candidates. The probability each candidate x_i is selected is

$$p(\mathbf{x}_i) = \frac{R(\mathbf{x}_i)}{\sum_{\mathbf{x}_j \in K} R(\mathbf{x}_j)}, \tag{6}$$

where $R(\mathbf{x}_i) = \sum_{\mathbf{x}_j \in K} d(\mathbf{x}_i, \mathbf{x}_j) = \sum_{\mathbf{x}_j \in K} ||\mathbf{x}_i - \mathbf{x}_j||$, and K represents the set consisting of all current fireworks and sparks.

The fireworks algorithm is originally considered as a swarm intelligence algorithm. However, its framework is quite different from other typical swarm intelligence algorithms, in which the population size is usually fixed (like PSO or ACO) or at least seems so (like ABC). While in evolutionary algorithms, the numbers of parents and offspring are different (like GA or ES). From this point of view, the FWA is more similar to evolutionary algorithms. However, it is also different from evolutionary algorithms, because it contains the idea that multiple fireworks interact and cooperate to accomplish global optimization. Therefore, the FWA should be considered as a developmental (evolutionary) swarm intelligence algorithm [157].

Tan et al. published an introduction [171] and a monograph [170] of the FWA in 2013 and 2015, respectively, which introduced the principles and typical applications of the algorithm in detail. While in this article, we summarize the literature of the FWA from 2010 to 2018. This is the first comprehensive review of the fireworks algorithm.

3 ALGORITHMIC RESEARCH

In this section, we review the literature about the algorithmic research of the FWA, including improvements of the FWA itself, hybridizations of the FWA and other algorithms, and adaptations of the FWA for multi-objective optimization or dynamic optimization problems. However, FWA variants for solving discrete optimization problems are reviewed along with the applications in Section 5, because in discrete/combinatorial optimization problems, how solutions are encoded is more problem related.

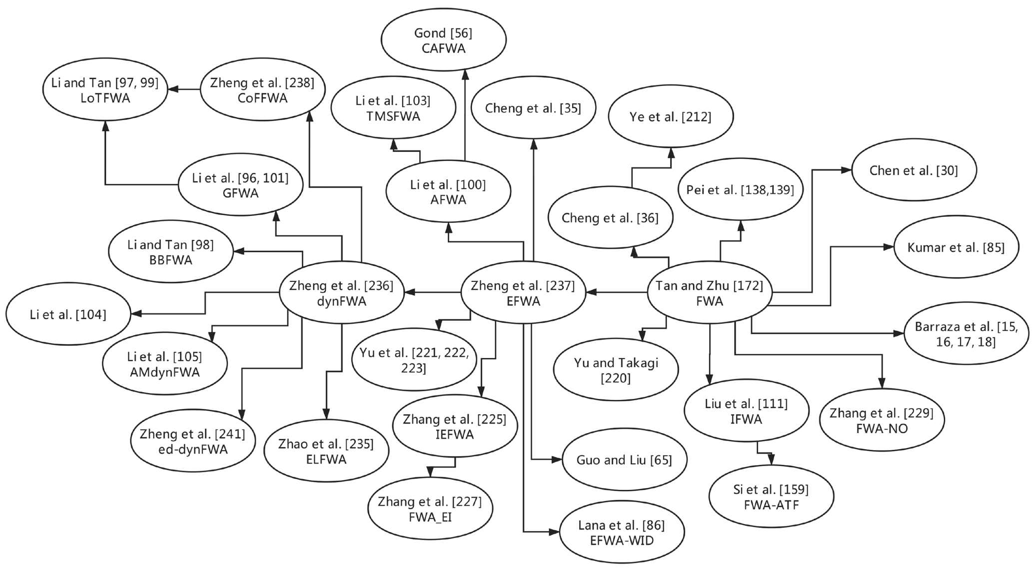

Fig. 1. Dendrogram of FWA variants.

3.1 Algorithmic Improvements

Figure 1 shows an overview of the variants of the FWA.

3.1.1 Operator Improvements. Zheng et al. [237] conducted a quite thorough analyses of the original FWA.

(1) According to the explosion operator in the original FWA (Algorithm 1), the displacement e remains unchanged in every dimension for a certain spark, which may limit the exploration ability of the algorithm. Therefore, they proposed that the displacement should take different random numbers in each dimension.
(2) According to Equation (4), the explosion amplitude of the firework with the best fitness is 0, which makes it unable to search effectively. Therefore, they proposed a minimal explosion amplitude check strategy to prevent the explosion amplitudes from being too small, in which the threshold of the explosion amplitudes is a (linearly or non-linearly) decreasing function of the number of evaluations.
(3) The mutation operator and the mapping rule in the original FWA are concentrated near the origin. Therefore, the performance may suffer greatly when the optimal point of the objective function is moved away from the origin. Therefore, they proposed a new kind of mutation operator and suggested a random mapping rule.
(4) The density-based selection operator is time-consuming. So they proposed replacing it with an elitism-random selection operator.

Based on these analyses and improvements, the enhanced fireworks algorithm (EFWA) is proposed. Experimental results on 12 different test functions with different shift values indicate that the performance of the EFWA is stable even when the objective function is shifted and that the computational cost of the EFWA is less than the original FWA.

Liu et al. [111] pointed out by experiments that the explosion amplitudes and the explosion sparks' number are unstable in the original FWA. They proposed using a rank-based transfer function to calculate A_i and λ_i. Besides, they, too, realized the problem in the mutation operator of the original FWA and therefore suggested using a pure-random mutation operator. They also pointed out that the density-based selection operator only considers the distance but not the fitness values of individuals, and therefore they proposed two kinds of alternatives: using a fitness-based roulette or greedily selecting the best ones. Experimental results on 14 of the functions of the CEC2005 benchmark indicate that the greedy selection outperforms the roulette and that the proposed improved FWA (IFWA) outperforms the original FWA, and its performance is comparable to PSO. Si et al. [159] proposed a new kind of transfer function based on the IFWA, in which not only the ranks but also the differences of fireworks' fitness are used. Experimental results on the CEC2013 benchmark indicate that the proposed algorithm (FWA-ATF) outperforms the original FWA, the EFWA, and the IFWA significantly.

Li et al. [100] and Zheng et al. [236] respectively proposed two different approaches to control the explosion amplitude adaptively (dynamically). They pointed out that the threshold in the minimal explosion amplitude check strategy in the EFWA is a manually set function, which cannot adapt to different objective functions and different search phases. Therefore, they proposed adaptive FWA (AFWA) and dynamic search FWA (dynFWA), respectively. Their core ideas and effects are similar [238]: In each generation, if a better solution is found, then the amplitude should be amplified; otherwise, it should be reduced. Besides, Zheng et al. also pointed out that the mutation operator in the EFWA is not effective in the dynFWA, and thus removed it. Experimental results on the 28 functions of the CEC2013 benchmark [108] indicate that both algorithms significantly outperform the EFWA and several PSO variants.

Zhang et al. [225] proposed a new mutation operator and a new selection operator based on the EFWA. In the new mutation operator, two individuals are chosen randomly, and a mutation spark is generated on the line connecting them. In the new selection operator, for each candidate, q opponents are randomly chosen from the whole population, and the fireworks of the next generation are the candidates that win most times. Experimental results on 18 test functions indicate that both improvements are effective and the proposed improved EFWA (IEFWA) outperforms the EFWA significantly. Later, they [227] hybridized the migration operator of bio-geography-based optimization (BBO) [160] with the explosion operator in the FWA. Experimental results on the CEC2015 benchmark [107] indicate that the EFWA with the three strategies (FWA_EI) outperforms the EFWA and BBO significantly.

Cheng et al. [36] too pointed out the problem of the mapping rule in the original FWA. Therefore, they tested four different kinds of mapping rules. Experimental results on shifted objective functions indicate that mapping to the boundary and mapping to limited stochastic region outperform other mapping rules. Ye et al. [212] explored the same topic in large-scale optimization. They found that the mirror mapping rule outperforms the others on most test functions.

Li et al. [104] proposed five improvements in the FWA. (1) In the initialization step, the fireworks and their opposition solutions are together evaluated, the better ones are taken as the fireworks in the first generation. (2) A dynamic explosion amplitude strategy is proposed, which is the same as in the dynFWA except that when all the fireworks are of the same fitness, the explosion amplitude will also be amplified. (3) The Gaussian distribution used in the mutation operator in the EFWA is replaced with a t-distribution. (4) The opposition solution of the best firework is introduced in the population as an elite solution. (5) Other than the best candidate, other fireworks are selected based on a special kind of roulette, in which good and bad candidates are of higher probability but medium candidates are of lower probability to be selected. The proposed algorithm proves to be globally convergent. Experimental results on the CEC2013 benchmark indicate that the proposed algorithm outperforms the original FWA, the EFWA, and the dynFWA significantly.

Li et al. [103] proposed a new displacement method based on the AFWA (which is unfortunately based on a misunderstanding of the AFWA) and an elitism-tournament selection operation. In the elitism-tournament selection operation, the best candidate is first selected. Then, each time two individuals are randomly chosen from the rest candidates, the better one is selected a firework. This process is repeated for $\mu - 1$ times. Experimental results on the CEC2015 benchmark indicate that the proposed TMSFWA outperforms the EFWA, the AFWA, and the dynFWA.

Li et al. [105] introduced an adaptive mutation into the dynFWA, i.e., using Lévy distribution in early phases and using Gaussian distribution in late phases. Experimental results on the CEC2013 benchmark indicate that the proposed algorithm (AMdynFWA) outperforms the EFWA, the AFWA, and the dynFWA significantly.

Yu and Takagi [220] proposed two improvements upon the original FWA. (1) The amplitudes are no longer allocated according to fitness values. Instead, the amplitudes of all fireworks are set to the same value that linearly decreases until a certain time, and remains unchanged after that. (2) A new selection mechanism similar to the independent selection is proposed, but the mutation operator is adopted and the mutation sparks are combined with the candidate pool of the worst firework. Experimental results on 20 of the test functions of the CEC2013 benchmark indicate that both proposed strategies are effective and the proposed algorithm outperforms the original FWA significantly.

Li and Tan [98] proposed a simplified version of the dynFWA, called bare bones FWA (BBFWA). In the BBFWA, only one firework is adopted, and the mutation operator and the dimension selection mechanism are all removed. Experimental results on the CEC2013 benchmark indicate that the BBFWA outperforms the EFWA, the AFWA, the dynFWA, the CoFFWA, and several other evolutionary algorithms, and the complexity of the BBFWA is smaller than these algorithms. Its performance on three of the real-world problems of the CEC2011 competition [38] is comparable to the champion of that competition.

Yu et al. [223] proposed generating sparks one by one, and each spark is generated around the former one except that the first one is generated around the firework. However, once the fitness of the new spark is worse than the former, this process stops and starts over from the firework. They also proposed a new selection strategy, which is different from the one in the EFWA in that the sparks whose fitness are worse than the firework are no longer considered as candidates. Experimental results on the CEC2013 benchmark indicate the proposed strategies improve the performance of the EFWA significantly.

Cheng et al. [35] proposed three improvements based on the EFWA. (1) They proposed a new explosion operator that can allegedly generate sparks in a spherical neighborhood of each firework. (2) They proposed a new mutation operator that allows all fireworks and sparks to have equal chances to generate mutation sparks. (3) A deep information exchange strategy that is borrowed from the Grey Wolf Optimizer (GWO) [128] is introduced to act on the candidate set. Experimental results on 23 test functions indicate the proposed algorithm outperforms the EFWA and several other opponents.

Guo and Liu [65] replaced the Gaussian sparks in the EFWA with a new kind of sparks that are generated around the middle point between the best fireworks and a randomly selected firework. Experimental results on 20 thirty-dimensional test functions indicate that the proposed improved EFWA outperforms both the EFWA and the dynFWA significantly.

Yu et al. [222] proposed a novel explosion paradigm called multi-layer explosion. In each explosion operation, after sparks are generated and evaluated, each spark will generate a certain number of subsequent sparks within certain amplitudes depending on the fitness of these sparks. In this way, more landscape information is utilized and the shape of the explosion becomes more flexible. Experimental results on the CEC2013 test suite indicate that the performance of the EFWA can be significantly improved using the proposed paradigm.

3.1.2 Elite Strategies. Pei et al. [138] introduced an elite strategy into the FWA. In every generation, a number of individuals are chosen to conduct fitness landscape approximation on each projected dimension. Then a promising elite spark is generated using the approximation. If its fitness is better than the worst individual, then the worst individual will be replaced with the elite spark. Experimental results on 10 of the test functions of the CEC2005 benchmark suite [166] indicate the effectiveness of the proposed method. Later, they [139] investigated different kinds of approximation approaches. Experimental results on all test functions of the CEC2005 benchmark indicate that approximation in low dimensional space is better than in higher dimensional or the original space, and individuals used for approximation should be chosen randomly from the population.

Li et al. [96, 101] pointed out that the information obtained by the explosion sparks is not fully used in the dynFWA. Therefore, they proposed an information utilization-based guiding mutation operator. By calculating the difference vector between good explosion sparks and bad explosion sparks, which is used to lead the movement of the fireworks, the convergence speed and the exploration capability can be enhanced. Experimental results on the CEC2013 benchmark indicate that the dimension selection mechanism in the explosion operator is not useful in the proposed guided FWA (GFWA), and the GFWA outperforms the EFWA, the AFWA, the dynFWA, and several other evolutionary algorithms significantly. Experimental results on the CEC2010 large-scale optimization benchmark [173] indicate that the performance of GFWA on large-scale problems (1,000 dimensions) is comparable to state-of-the-art large-scale optimization algorithms.

Yu et al. [221] proposed another elite strategy based on the EFWA. First, each firework and the sparks it generated are used to calculate a gradient-like vector, which is a weighted sum of the differences between the firework and each spark. Second, the vectors are used to estimate a convergence point, which will be finally introduced into the population and take the place of the worst candidate if its fitness is better. Experimental results on 20 of the CEC2013 test functions indicate the performance of the proposed algorithm outperforms the EFWA significantly.

3.1.3 Interactive Mechanisms. Zheng et al. [238] showed experimentally that the fireworks other than the best one contribute little to the search process, because the fireworks are selected from the same candidate pool, which makes the information of bad fireworks not inherited. Therefore, they proposed an independent selection framework, in which each firework is selected from its own offsprings. Besides, they also proposed a crowdedness-avoiding strategy to prevent other fireworks to search the same local area with the best firework. Experimental results on the CEC2013 benchmark indicate that the mutation operation in the EFWA is not useful either in the dynFWA or the AFWA, and thus it is removed in the proposed cooperative framework FWA (CoFFWA). Judging from the average ranks, the CoFFWA outperforms the EFWA, the AFWA, and the dynFWA and several other swarm intelligence algorithms.

Zhao et al. [235] proposed three improvements based on the dynFWA. (1) The explosion sparks' number of the best firework is no longer calculated according to Equation (2). Instead, it is set to a fixed number. (2) The other fireworks will be reinitialized with a certain probability and move toward the best one. (3) A mirror mapping rule is adopted instead of the random mapping rule. Experimental results on the CEC2015 benchmark indicate that the proposed elite-leading FWA (ELFWA) outperforms the dynFWA, the dynFWACM, and the eddynFWA.

Laña et al. [86] introduced a wind inertia dynamics into the EFWA to force generated sparks to move toward the best firework. Experimental results on six test functions indicate that the proposed algorithm (EFWA-WID) outperforms the EFWA significantly.

Li and Tan [97, 99] proposed a loser-out tournament-based fireworks algorithm based on the independent selection framework, in which if the fitness of a firework cannot catch up with the best one, it will reinitialized to elevate the probability of avoiding local optima. Experimental results on the CEC2013 benchmark indicate that the loser-out tournament-based FWA (LoTFWA) outperforms the EFWA, the AFWA, the dynFWA, the CoFFWA, and the GFWA on multi-modal test functions significantly, and, according to average ranks, the LoTFWA also outperforms restart CMA-ES with increasing population (IPOP-CMAES) [9] on multi-modal test functions.

3.1.4 Other Work. Zheng et al. [241] showed by experiments based on the dynFWA that with smaller z (i.e., fewer explosion dimensions) in the explosion operator, the generated explosion sparks have a greater chance to surpass the firework. Therefore, they proposed reducing the number of explosion dimensions by a certain coefficient after every certain number of generations. Experimental results of the proposed algorithm (ed-dynFWA) on the CEC2015 benchmark are shown, but no comparison was made against other algorithms.

Chen et al. [30] proposed an approach to balance exploration and exploitation in the original FWA by utilizing landscape information. If the coverage of the sparks is large, then the sparks are generated randomly in the next generation. If the coverage is middle, then sparks are generated by utilizing landscape information. Otherwise, sparks are generated in the original way. Experimental results on eight test functions indicate the proposed algorithm outperforms the original FWA and the EFWA.

Kumar et al. [85] evaluated the original FWA on six test functions and obtained the optimal parameter setting on these problems.

Barraza et al. [15, 16, 18] proposed using fuzzy logic to dynamically adjust the number of explosion sparks and explosion amplitudes. According to different search phases, the total amplitude and number of explosion sparks are subject to different membership functions. Experimental results on 12 test functions indicate that the proposed algorithm (IFFWA) outperforms the original FWA significantly. Later, they [17] introduced a new kind of input into the fuzzy system called sparks dispersion measure. Experimental results on 14 test functions with different shift values indicate that the new algorithm (DPIFFWA) outperforms the IFFWA significantly.

Gong [56] proposed using chaotic maps to control the amplification coefficient in the AFWA. Experimental results on 12 shifted test functions indicate that the circle map–based chaotic AFWA (CAFWA) outperforms the AFWA significantly, and according to average ranks, the CAFWA outperforms the original FWA, the EFWA, and several other swarm intelligence algorithms.

Zhang et al. [229] proposed a resampling-based FWA for noisy optimization problems. The core idea is enlarging the number of top sparks resampled while reducing the number of resampling times with the search process. Experimental results on the CEC2015 benchmark with different noise levels indicate that the proposed algorithm (FWA-NO) outperforms CoFFWA and its simple resampling versions.

3.2 Hybrid Algorithms

Yu et al. [215, 218] replaced the mutation operator in the EFWA with the mutation strategy in differential evolution (DE). Experimental results on the CEC2014 benchmark [106] indicate that the proposed EFWA with differential mutation (FWA-DM) outperforms the EFWA significantly.

Zheng et al. [243] proposed another kind of hybrid algorithm of the FWA and DE. After sparks are generated, μ individuals are selected from the best individuals using roulette. Then DE operators are conducted upon the μ individuals to generate trail solutions, which will replace the original ones if they are of better fitness. After the new μ solutions are the fireworks of the next generation. Experimental results on eight test functions show the advantage of the hybrid algorithm over the both components.

Yu et al. [216, 217, 219] successively introduced a covariance mutation into the AFWA, the dynFWA, and the CoFFWA. Experimental results on the CEC2015 benchmark indicate that the AFWA with covariance mutation (FWA-CM) outperforms the AFWA significantly.

Gao et al. [53] combines the FWA with the opposition-based learning and quantum computing operators. Experimental results on five test functions indicate that the proposed opposition-based quantum FWA (OQFWA) outperforms the original FWA.

Bacanin et al. [12] used the search manner in the firefly algorithm to replace the mutation operator in the original fireworks algorithm. Experimental results on six test functions indicate that the proposed algorithm outperforms the original FWA and several PSO variants, while Wang et al. [192] introduce the explosion operator into the firefly algorithm to improve its local search. Experimental results on the CEC2013 suite indicate that the proposed hybrid algorithm outperforms the FWA and variants of the firefly algorithm.

Gong [57] combines the AFWA with opposition-based learning. In the initialization step, the fireworks and their opposition solutions are together evaluated, and the better ones are taken as the fireworks in the first generation. In each generation, with a certain probability, the quasi opposites of selected fireworks are also evaluated, and the fittest ones among fireworks and their quasi opposites are the fireworks of the next generation. Experimental results on 12 test functions indicate that the proposed opposition-based adaptive fireworks algorithm (OAFWA) outperforms the AFWA significantly.

Sun et al. [168] introduced the grouping strategy of the shuffled frog leaping algorithm (SFLA) [48] into the original FWA. Experimental results on four test functions indicate that the hybrid algorithm outperforms both the original FWA and the SFLA.

Ye and Wen [211] proposed using the simulated annealing factor to replace the minimal explosion amplitude check strategy proposed in EFWA. Experimental results on five of the test functions of the CEC2013 benchmark and three of the test functions of the CEC2014 benchmark indicate that the hybrid algorithm outperforms the double elite co-evolutionary genetic algorithm and the differential evolution algorithm based on self-adapting mountain-climbing operator.

Chen [31] proposed a hybrid algorithm of PSO and the FWA, in which the operators of PSO are used for exploration, while the operators of the FWA are used for exploitation. Experimental results on 22 test functions indicate the hybrid algorithm (PS-FWA) outperforms PSO and the original FWA.

Barraza et al. [19] proposed a hybrid algorithm of the FWA and GWO, in which the initialization is conducted using the explosive manner. Experimental results on 22 test functions indicate the hybrid algorithm performs well when the dimensionality is low.

Two different groups proposed two versions of hybridization of BBO and the FWA. Zhang et al. [226] selected the operators of the EFWA and BBO by a certain probability in each iteration, while Farswan and Bansal [49] used the operators of BBO and the original FWA in turn in each iteration. Both hybridizations are evaluated and shown effective on a number of test functions.

3.3 Dynamic Optimization

Pekdemir and Topcuoglu [140] proposed two variants of the EFWA for dynamic optimization problems. In the EFWA-D1, explosion sparks' numbers and explosion amplitudes of all fireworks changes over iterations by rates of 1.1 and 0.9, respectively; mutation operator is removed; and independent selection is adopted. The only difference between the EFWA-D1 and the EFWA-D2 is that a simplified adaptive amplitude takes the place of the exponentially decreased amplitude. Experimental results indicate that the performances of both algorithms measured by offline error are better than that of some previous dynamic optimization techniques including hyper-mutation, random immigrants, memory search and self-organization scouts.

3.4 Multi-objective Optimization

Liu et al. [113] proposed a multi-objective FWA based on the S-metric. There are two main modifications based on the original FWA. (1) The candidates with the largest S-metrics are selected as the fireworks of the next generations. (2) An external archive is adopted to maintain the best solution set. In each generation, when updating the archive, the individuals with the smallest S-metrics are removed one by one. Experimental results on six multi-objective test problems indicate that the proposed algorithm (S-MOFWA) outperforms NSGA-II, SPEA-2, and PESA-2.

Bejinariu et al. [21] proposed two different approaches to extending the FWA to solve multi-objective problems: (1) scalarization, i.e., transforming a multi-objective optimization problem into a single-objective optimization problem in which the object is computed as a weighted sum of the objective functions, and (2) random selection of non-dominated solutions as the fireworks. Experimental results on one multi-objective problem are shown, but there is no comparison against other algorithms.

Chen et al. [32] proposed a hybrid multi-objective optimization algorithm based on the MOEA/D framework [231], which is composed of an offspring generation method and two different replacement strategies. In the proposed algorithm, the explosion operator and the Gaussian mutation operator of the FWA are used for generating offspring. Experimental results on 19 test functions show the advantage of the proposed algorithm over several other MOEA/D variants.

4 THEORETICAL ANALYSES

Liu et al. [112] conducted analyses on the convergence and the time complexity of the FWA. By considering the FWA as a Markov stochastic process, they pointed out that the original FWA is globally convergent (because it contains a global random mutation operator) and they also gave estimation of its convergence time.

Using a similar procedure as in Reference [112], Li et al. [104] also gave proof of global convergence of their improved FWA. While Gao et al. [52] gives another kind of proof for their algorithm, which shows that the population's probability density function should be closely concentrated near the objective function's global optimal value after sufficient iterations.

Li et al. [101] analyzed the properties of the guiding mutation operator on a (basically) two-dimensional objective function. They pointed out that (1) the length of the guiding vector is relatively short on irrelevant directions, and therefore the direction is accurate, and (2) the length of the guiding vector is relatively long on relevant directions if the local optimum is outside the explosion amplitude and short otherwise. Therefore, the step size of the mutation operator is adaptive to different search processes.

Li and Tan [98] gave sufficient conditions of local convergence of the BBFWA. According to their analyses, the sufficient condition can be relaxed when the amplification coefficient is adopted, which justifies the design of the dynamic explosion amplitude. Moreover, generating more sparks is helpful to avoiding premature convergence.

5 APPLICATIONS

So far, different versions of the FWA have been applied in a wide range of real-world problems, which are summarized in Table 1.

5.1 Supervised Learning

He et al. [67] used the FWA to "optimize the parameters of a local-concentration model for spam detection." Zheng and Tan [240] used the FWA, PSO, and DE to optimize the parameters of a unified distance measure for palmprint and finger-vein identification. Lihu and Holban [109] used the FWA to maximize the Kullback-Leibler divergence between candidate motifs. Alamaniotis et al. [2, 3] used the original FWA to optimize the coefficients of "a linear combination of known template signature patterns" for radioisotopic identification. Gonsalves [58] used the FWA to optimize the feature subset for software cost estimation. Ma and Niu [121] used the FWA to optimize the feature subset for icing forecasting of high voltage transmission line. Sreeja [161] proposed a weighted pattern matching approach for imbalanced classification in which the FWA is adopted for feature and weight optimization. Tuba et al. [184] used the EFWA to optimize the parameters of the support vector machine, whose performance was demonstrated on standard datasets. Duan et al. [46] used the FWA to optimize the coefficients of the twin support vector regression prediction model for basic oxygen steelmaking endpoint prediction. Zhang et al. [230] used the original FWA to optimize the parameters of the multiclass support vector machine for the task of unnatural control chart pattern recognition. Lei et al. [92] used the BBFWA to optimize the least squares support vector machine for short-term power load forecasting. Khuat and Le [82] used the FWA to train the feed forward neural network at the beginning stage (continued with the Levenberq-Marquardt algorithm) for the task of agile software effort prediction. Dutta et al. [47] and Salman et al. [151] respectively used the FWA to optimize the feed forward neural network for classification tasks in medical data processing. Khuat et al. [83, 84] used the FWA to train the feed forward neural network at the beginning stage (continued with the back-propagation algorithm) for the task of stock price estimation. Suksri and Kimpan [167] used the FWA to train the feed forward neural network for weather forecasting. Gonsalves [59] used PSO and the EFWA to train feed forward neural networks for classification tasks. Bolaji et al. [24] used the FWA to train the feed forward neural network for classification tasks. Zhang J. and Zhang H. [228] used the FWA to train a three-layer neural network for predicting short-time traffic flow. Xue et al. [204–206] used the FWA to train a linear model for classification tasks. Zalasiński et al. [224] used the FWA to train a fuzzy system for predicting values of features describing the dynamic signature. Tao and Ye [175] used the FWA to optimize a Gaussian process regression model for WiFi indoor positioning.

5.2 Unsupervised Learning

Yang and Tan [209] used the FWA and several other evolutionary algorithms to initialize k-means for document clustering. Karimov and Ozbayoglu [79] proposed a hybrid algorithm of cuckoo search and the EFWA to initialize k-means for big data clustering. Mattos et al. [125] evaluated several meta-heuristics including the FWA for clustering of supply chain data. Tuba et al. [179] to BBFWA to optimize the centers in k-means in the first iteration for web data clustering. Liu et al. [110] proposed a discrete FWA to optimize the number of clusters along with the cluster-heads in wireless sensor clustering. Bouarara et al. [25] proposed a framework using the fireworks algorithm to optimize query-document relevance for automatic web information retrieval. Si [158] used the fireworks algorithm for evolving computer programs automatically. Guendouz et al. [63] proposed a discrete version of the FWA for community detection in complex networks. Ma and Xia [122] proposed another approach for community detection based on a discrete FWA with local double ring initialization.

5.3 Scheduling/Routing

Zheng et al. [242] proposed a multi-objective version of the FWA to optimize the dosage of fertilizers. Several groups of researchers [4, 68–70, 93, 130, 132, 133, 234] proposed or adopted different variants of the FWA to minimize power loss in network reconfiguration. Abdulmajeed and Ayob [1] and Yang and Ke [207], respectively, adapted the FWA to solve the capacitated vehicle routing problems. Cai et al. [27] established a model of "the vehicle routing problem with multiple time windows" and proposed a quantum fireworks evolutionary algorithm to solve it. Bacanin and Tuba

[11] adapted the FWA for constrained portfolio investment based on the extended mean-variance model. Zhang and Liu [233] also used the FWA to optimize portfolio investment, but this is based on the classical mean-variance model. Liu et al. [116] proposed a binary version of the FWA for multi-satellite control resource scheduling. Tuba et al. [162, 189, 190] proposed several approaches for RFID planning based on different versions of the FWA. Kumar et al. [136, 146–149, 153] proposed a binary FWA to solve the thermal unit commitment problem with constraints. Yang et al. [208] proposed a multi-objective FWA to find services in the task of data-intensive service mashup. Tuba et al. [8, 182, 183, 186], Liu et al. [115], and Xia et al. [197] used the FWA to find optimal sensor nodes positions that covers the area of interest maximally. Wei et al. [196] proposed a multi-objective discrete FWA for charging path planning of wireless rechargeable sensor networks. Ding et al. [40] designed a tourist recommender system and proposed a discrete FWA to solve optimize the tourist trip. Li and Lu [102, 118] proposed a discrete FWA for assembly sequence planning. Zhang et al. [232] and Liu et al. [117] proposed two discrete FWAs to solve the satellite link scheduling problem. Shi et al. [154] used the FWA to solve "the load balancing problem in the software defined cloud-fog network." Alihodzic [5, 6] used the FWA and the GFWA, respectively, for unmanned aerial vehicle path planning. While Wang et al. [193] proposed a hyper-heuristic integrating GA, PSO, BBO, FWA, and WWO to solve the same problem. Jadoun et al. [71, 72, 135] proposed an improved FWA to solve the economic dispatch problem. Xue et al. [203] proposed a discrete fireworks algorithm to solve the aircraft mission planning problem. Pavão et al. [137] proposed a two level optimization approach based on simulated annealing and a novel rocket FWA to optimize the heat exchanger network. Ye et al. [210] introduced local search and chaotic mutation mechanisms in the FWA to solve the warehouse-scheduling problem. Wang et al. [194] proposed a multi-objective hybrid algorithm of the FWA and gravitational search to solve the economic and environmental operation management problem. Mnif and Bouamama [129] proposed a multi-objective FWA to solve the multimodal transportation problem. Fu et al. [50] proposed a multi-objective discrete FWA for the stochastic flow-shop scheduling. Ting et al. [176] used the FWA for hybrid flow shop scheduling. Bahramian-Habil et al. [13] proposed a multi-objective FWA for fault current limiter placement. Guo et al. [66] proposed a discrete multi-objective FWA for software project scheduling. Li et al. [95] proposed an improved FWA for multi-core processor scheduling.

5.4 Numerical Calculation

Janecek and Tan [73–76] used several evolutionary algorithms including the FWA for the initialization of the nonnegative matrix factorization. Zheng et al. [239] evaluated several versions of the FWA on the ICSI2014 numerical optimization benchmark suite. Li et al. [94] used several versions of the FWA to optimize the parameters in the chaotic system. Reddy et al. [144, 145] used the FWA to estimate the control points for Bezier curves/surfaces fitting. Guan et al. [62] used the FWA to optimize the nodes in the integral interval for numerical integration. Mu et al. [131] introduced a linearly decreased dimension number strategy in the dynFWA and parallelized it to find the optimal perturbation of a nonlinear model.

5.5 Design/Control

Gao and Diao [51] proposed a hybrid algorithm of the FWA and the culture algorithm for digital filter design. Pholdee and Bureerat [141] compared the performances of several different evolutionary algorithms on the task of truss mass minimization with dynamic constraints. While Gholizadeh and Milany [54] proposed an improved fireworks algorithm for both truss and frame structure optimization tasks. Rajaram et al. [143] tested the firefly algorithm and the FWA on the task of selective harmonic elimination in inverter output waveforms. Goswami and Chakraborty [61] tested the FWA and cuckoo search for the parametric optimization of laser machining processes. Later,

(a) Original Image

(b) Compressed by Recommended Q_{10} Quantization Table

(c) Compressed by the Quantization Table Optimized by the GFWA

Fig. 2. GFWA for JPEG quantization table optimization.

the same authors [60] tested the FWA and gravitational search for the parametric optimization of ultrasonic machining processes. Babu et al. [10] used the FWA to optimize the parameters of the solar photovoltaic model. Several groups of researchers [88, 163–165, 202, 213] used the FWA to optimize the parameters of the proportional-integral-derivative controller. BouDaher and Hoorfar [26] and Tang et al. [174] used the FWA for electromagnetic and antenna optimization. Fortes et al. [39] used the FWA to optimize parameters of the supplementary damping controllers. Manickam et al. [124] and Sangeetha et al. [152] used the FWA for maximum power point tracking in the photovoltaic system. Dou et al. [45] used the AFWA for inverse analysis of concrete dams. Guerreiro et al. [64], Amhaimar et al. [7], and Basílio [20], respectively, used the FWA to optimize the design of orthogonal frequency division multiplexing schemes. Yin et al. [195, 214] respectively proposed variants of the AFWA to optimize parameters for the control of hypersonic vehicles. Gao et al. [52] proposed a hybrid algorithm of the FWA and quantum computation to find the optimal cooperative mechanism of energy harvesting cognitive radio. Karkalos et al. [80] used the FWA to optimize the parameters of the constitutive material model for stainless steel. Xie et al. [199] proposed a hybrid algorithm of the FWA and PSO to improve the crashworthiness of subway vehicles. Jeronymo et al. [77] proposed an improved FWA combined with free search and opposition-based learning for the design of a spiral inductor. Pallone et al. [134] adapted the EFWA to optimize the ascent path of multistage launch vehicles.

5.6 Image Processing

Tuba et al. [188], Chen et al. [28, 114], and Chen et al. [34], respectively, used the FWA to optimize the threshold values in image segmentation. Rahmani et al. [142] proposed an explosive image perturbation approach for privacy preserving. Shi et al. [155, 156] proposed a modified FWA that adopts different displacements on different dimensions to locate multiple cells in microscopy images. Bejinariu et al. [22] and Tuba et al. [181, 185] used the FWA for image registration. Bejinariu et al. [23] tested PSO, cuckoo search and the FWA on the task of image fusion. Tuba et al. [178, 187] used the GFWA and the BBFWA, respectively, to optimize the JPEG quantization table in image compression (see Figure 2). Wang et al. [191] used the FWA to optimize the conventional neural network for image retrieval.

5.7 Others

Ding et al. [33, 41] used several different evolutionary algorithms for seismic waveform inversion. Ren et al. [150] proposed a velocity-based improved FWA to estimate the thermal and optical properties of molten salt. Crawford et al. [37] and Tuba et al. [177] used different variants of the FWA to solve the set covering problem. Taidi et al. [169] and Luo et al. [120] proposed discrete FWAs to solve the travelling salesman problem. Xue et al. [201] proposed an uncertain bilevel knapsack problem and proposed a binary backward FWA for solving it. Lee [90, 91] proposed a modified FWA for the inverse scattering of a conducting cylinder. Łapa [87] proposed a hyper-heuristic integrating several evolutionary operators, including explosion and mutation operators of the FWA for non-linear modeling. Later, Łapa et al. [89] proposed a fuzzy system-based approach for non-linear modeling, in which a hybrid algorithm of the GA and the FWA is used to optimize the structure and parameters. Xiao et al. [198] used the EFWA to locate the critical slip surface with the minimal safety factor in slope stability analysis. Ma et al. [123] used the AFWA for minefield attack decision. Tuba et al. [180] used the BBFWA to solve the capacitated p-median problem. Miao et al. [126] modified the FWA to solve the problem of mobile robot odor source localization. Chen et al. [29] compared the performances of the complete algorithm, the heuristic algorithm and the FWA on the problem of for task-oriented satellite agent team formation.

6 IMPLEMENTATIONS

6.1 Parallelization

Ding et al. [43] proposed the the first parallel framework of the FWA implemented on GPU, which enjoys a speedup as high as 200× with the expense that the fireworks cannot exchange information frequently. To guarantee the quality of the solutions, they proposed an attract-repulse mutation operator to enhance the performance, which is similar to the Gaussian mutation in the EFWA but the distribution is uniform. Experimental results indicate that the proposed GPU-FWA not only outruns the original FWA and PSO but also outperforms them. Later, Ding and Tan [42] further elevated the performance by introducing the dynamic explosion amplitude and a Cauchy mutation operator into the GPU-FWA.

Ludwig and Dawar [119] implemented the EFWA using the MapReduce platform. Experimental results performed on different benchmark functions indicate that the EFWA achieves a better speedup rate than PSO on the MapReduce framework, which concurs with the finding in Reference [43].

6.2 Others

Baidoo [14] implemented a Java version of the FWA with a simple user interface.

Different versions of the FWA have also been implemented in MATLAB, C, Java, C++, Python, and so on. Please visit http://www.cil.pku.edu.cn/research/fwa/resources/index.html for more information.

7 DISCUSSION

Figure 3 shows the number of the literatures of the FWA in recent years. It can be seen that the FWA has been attracting more and more research interest and has been used to solve more and more real-world problems. Among all the literature, the number of applications is the most, followed by algorithmic research.

7.1 Algorithmic Research

Most algorithmic studies of the FWA place their focus on single objective optimization, which is the basis of multi-objective optimization and applications. Improving the FWA itself and hybridizing it with other algorithms are both valuable and important as long as the performance can be elevated. Actually, algorithmic research on the FWA has gone deeper and deeper in

Table 1. Applications of the FWA

Supervised Learning	spam detection [67], palmprint and finger-vein identification [240], de novo motif prediction [109], gamma-ray spectrum analysis [2, 3], feature subset optimization [58, 121, 161], support vector machine parameters optimization [46, 92, 184, 230], artificial neural network training [24, 47, 59, 82–84, 151, 167, 228], linear model training [204–206], prediction of values of the dynamic signature features [224], Gaussian process regression model training [175]
Unsupervised Learning	clustering [79, 110, 125, 179, 209], web information retrieval [25], grammatical evolution [158], community detection [63, 122]
Scheduling / Routing	fertilization in oil crop production [242], power system reconfiguration [4, 68–70, 93, 130, 132, 133, 234], vehicle routing [1, 27, 207], portfolio optimization [11, 233], multi-satellite control resource scheduling [116], RFID network planning [162, 189, 190], thermal unit commitment [136, 146–148, 149, 153], data-intensive service mashup [208], wireless sensor network [8, 115, 182, 183, 186, 196, 197], tourist route planning [40], assembly sequence planning [102, 118], satellite link scheduling [117, 232], load balancing for cloud-fog network [154], UAV path planning [5, 6, 193], economic dispatch [71, 72, 135], aircraft mission planning [203], heat exchanger networks synthesis [137], warehouse scheduling [210], economic/environmental operation management [194], multimodal transportation [129], flow-shop scheduling [50, 176], fault current limiter placement [13], software project scheduling [66], multi-core processor scheduling [95]
Numerical Calculation	nonnegative matrix factorization [73–76], numerical optimization [239], parameter estimation of chaotic systems [94], fitting of Bezier curves/surfaces [144, 145], numerical integration [62], conditional nonlinear optimal perturbation [131]
Design / Control	digital filters design [51], truss/frame structure optimization [54, 141], selective harmonic elimination in PWM inverter [143], laser machining process [61], ultrasonic machining process [60], parameter extraction of two diode solar PV model [10], PID parameter optimization [88, 163–165, 202, 213], antenna design [26, 174], supplementary damping controller design [39], maximum power point tracking in PV systems [124, 152], parameter identification of concrete dams [45], critical slip surface locating [198], design of nonlinear OFDM [7, 20, 64], control of hypersonic vehicles [195, 214], optimization of energy harvesting cognitive radio [52], determination of Johnson-Cook material model parameters [80], improvement of the crashworthiness of subway vehicles [199], design of a spiral inductor [77], optimization of the ascent path of multistage launch vehicles [134]
Image Processing	multilevel image thresholding [28, 34, 114, 188], privacy preserving through image perturbation [142], cells tracking [155, 156], image registration [22, 181, 185], image fusion [23], image compression [178, 187], image retrieval [191]
Others	seismic waveform inversion [33, 41], estimation of thermal and optical properties of molten salt [150], set covering problem [37], maximal covering location problem [177] travelling salesman problem [120, 169], knapsack problem [201], inverse scattering of a conducting cylinder [90, 91], nonlinear modeling [87, 89], slope stability analysis [198], minefield attack decision [123], capacitated p-median problem [180], mobile robot odor source localization [126], task-oriented satellite agent team formation [29]

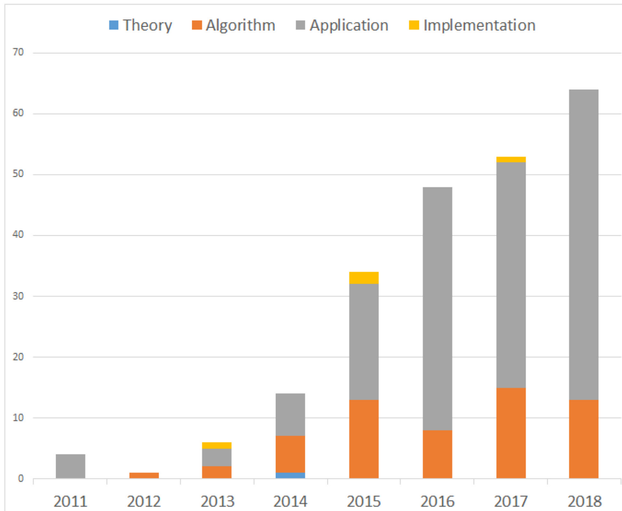

Fig. 3. Number of literatures of the FWA.

several different directions recently, such as improvements of the operators, novel cooperative mechanisms among fireworks, strategies for generating elite solutions, and more thorough utilization of the information. However, it can also be seen from this review that some of the studies are not based on competent knowledge of the field of FWA research. For example, some recent studies are still based on the original FWA, which is of several obvious drawbacks. It is part of the purpose of this review to provide a full picture for new researchers and avoid wasteful efforts. Here we provide the following suggestions to help them make a solid contribution.

(1) If you want to improve the FWA, then please choose a state-of-the-art version as the baseline algorithm rather than the original FWA.
(2) Make sure your benchmark is wide enough and shifted. The most convenient way is to use standard benchmarks.
(3) Try to provide hints about when your algorithm performs well, and when your algorithm performs not well. Because there is no cure-for-all.
(4) Conduct statistical tests to show the significance of your improvement.
(5) If you are trying to design a hybrid algorithm, then make sure your hybrid algorithm outperforms all component algorithms significantly.

Constraint handling is one of the most important topics in optimization. However, although some discussions have been conducted on the mapping rules of the FWA (which is used to handle boundary constraints), there are not enough studies on handling equality or other inequality constraints. According to the framework of the FWA, other inequality constraints can be handled by new kinds of mapping rules, while handling equality constraints may require new kinds of explosion/mutation operators.

How to solve multi-objective optimization and dynamic optimization problems using the FWA are also relatively new issues and deserve more attention in the future. Currently, multi-objective and dynamic FWAs can outperform classic methods on standard test functions, which has preliminarily shown its potential. Existing studies have also shown that designing new problem-solving frameworks using the principles of the FWA, and integrating the FWA into existing frameworks (like MOEA/D) are both feasible approaches.

Due to the unique framework of the FWA, we think its algorithmic research should be very attractive and challenging, because it may be able to solve problems that other algorithms cannot.

7.2 Theoretical Analyses

Theoretical analyses are of great importance, because they are supposed to construct the foundation of algorithmic research. However, the number of theoretical analyses of the FWA is limited due to its complex stochastic behaviors. There is only one completely theoretical paper regarding the convergence and time complexity of the original FWA, though theoretical analyses of other FWA variants can also be found in the literature such as References [101, 104] and Reference [98]. Further research is needed regarding the convergence properties (especially the convergence speed) and the dynamics of the FWA.

7.3 Applications and Implementations

The FWA has already been successfully applied in many different fields. Recently, many new versions of the FWA are proposed along with their applications in certain fields, which is in our opinion a very good trend. Because no algorithmic research should be conducted without usage scenarios. However, so far most of the applications are based on early versions of the FWA. We expect more evaluations of its improved versions on real-world problems in the future. We also encourage applications of the FWA on large-scale tasks, especially in big data processing and analyses, taking advantage of the efficiency and parallelizability of the FWA.

The FWA is of a unique framework, with competitive performance and high efficiency and parallelizability. We believe it will continue to attract more research interest and benefit the world in the future.

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