

## Chapter 2

# Last-Position Elimination-Based Fireworks Algorithm for Function Optimization

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### **ABSTRACT**

*Fireworks algorithm (FWA) searches the global optimum by the cooperation between the firework with the best fitness named as core firework (CF) and the other non-CFs. Loser-out tournament-based fireworks algorithm (LoTFWA) uses competition as a new manner of interaction. If the fitness of a firework cannot catch up with the best one, it is considered a loser and will be reinitialized. However, its independent selection operator may prevent non-CFs from aggregating to CF in the late search phase if they fall into different local optima. This chapter proposes a last-position, elimination-based fireworks algorithm which allocates more fireworks in the initial process to search. Then for every fixed number of generations, the firework with the worst fitness is eliminated and its sparks is reallocated to other fireworks. In the final stage of search, only CF survives with all the budget of sparks and thus the aggregation of non-CFs to CF is ensured. Experimental results performed show that the proposed algorithm significantly outperforms most of the state-of-the-art FWA variants.*

## INTRODUCTION

Optimization problems play an important role in a scientific research field. In the past two decades, many stochastic and population-based optimization algorithms based on Swarm Intelligence (SI) (Dong & Zhou, 2016) (Gu, Yu & Hu, 2017) (Han et al., 2015) (Mareda, Gaudard & Romerio, 2017) were proposed. These algorithms have shown great success for solving optimization problems in many applications. Most of SI algorithms are inspired by some intelligent colony behaviors in nature like particle swarm optimization (PSO) (Eberhart, R., & Kennedy, J., 1995, October). Different from these algorithms, fireworks algorithm (FWA) proposed by Tan & Zhu (2010, June), as a rising SI optimization algorithm, is inspired by the explosion process of fireworks in the sky. In this algorithm, the explosion process of a firework can be considered as a search by the sparks in the local area around a specific point where the firework is set off. In order to balance exploration and exploitation, the better a firework's fitness is, the more sparks it generates and the smaller its explosion amplitude is, and vice versa. In recent years, many improved versions of FWA have been presented. Zheng, Janecek & Tan (2013, June) propose an enhanced fireworks algorithm (EFWA) with five modifications to FWA. Among these improvements, the selection operator is widely adopted. It employs an elitism-random selection method to select the candidate with the best fitness as a firework at first, and then chooses the rest randomly among all the individuals in current population. This operator decreases the time complexity while maintaining the performance similar to that of the original one. Based on the work of EFWA, Zheng, Janecek, Li & Tan (2014, July) propose the dynamic search fireworks algorithm (dynFWA). In it, the firework with best fitness in each generation is called core firework (CF) and others are called non-core fireworks (non-CFs). It uses a dynamic explosion amplitude for CF, while non-CFs use the same strategy as that in EFWA. Li, Zheng & Tan (2014, July) present an adaptive fireworks algorithm (AFWA) by using adaptive amplitude. In AFWA, explosion amplitude is calculated according to the already evaluated fitness of individuals adaptively. Li, Zheng & Tan (2016) propose a guided fireworks algorithm (GFWA) by introducing a novel guiding spark to improve FWA performance. Its idea is to use the objective function information acquired by explosion sparks to construct a guiding vector with a promising direction and adaptive length, and to generate an elite solution called a guiding spark by adding the guiding vector to the position of each firework.

Although many FWA variants are developed from EFWA, its dependent selection operator makes CF absorb non-CFs into its search range quickly and may result in premature convergence. To overcome this limitation, Zheng, Li, Janecek & Tan (2017) propose a cooperative framework for fireworks algorithm (CoFFWA) which can greatly enhance the exploitation ability of non-CFs by using an independent selection operator and increase the exploration capacity by a crowding-avoiding cooperative strategy among the fireworks. Li & Tan (2017) propose a loser-out tournament-based fireworks algorithm (LoTFWA) which also utilizes an independent selection operator to select fireworks for the next generation. In LoTFWA, fireworks compete with each other and the losers will be forced to restart from a new location. The competitive mechanism is based on the anticipation of fireworks' fitness. If the fitness of a firework cannot catch up with the best one with its current progress rate, then this firework is considered a loser and will be reinitialized to avoid wasting resources on searching unpromising areas.

From aforementioned algorithms, LoTFWA is a novel variant characterized by using competition as a new manner of interaction. Benefit from this mechanism, LoTFWA achieves better performance than other fireworks algorithms. However, its independent selection operator may prevent non-CFs from aggregating to CF in the late evolutionary stage. This chapter proposes a novel Last-position Elimination-

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