Competitive Parallel Animated Oat Optimization Algorithm

1st Libin Fu
College of Computer Science and Engineering, Shandong University of Science and Technology
Qingdao, China
fulibin@sdust.edu.cn

2nd Shu-Chuan Chu
School of Artificial Intelligence, Nanjing University of Information Science and Technology
Nanjing, China
scchu0803@gmail.com

3rd Jeng-Shyang Pan*
College of Computer Science and Engineering, Shandong University of Science and Technology
Qingdao, China
Department of Information Management, Chaoyang University of Technology
Taichung, Taiwan
jengshyangpan@gmail.com

***Abstract*—This paper presents an enhanced version of the Animated Oat Optimization (AOO) algorithm, a novel evolutionary metaheuristic inspired by the rolling and propagation mechanisms of oat seeds in humid environments. To improve its performance, we integrate a parallel co-evolutionary framework with novel communication strategies to facilitate collaboration among subpopulations. Furthermore, a competitive strategy with an incentive mechanism is introduced to promote the evolution of high-quality solutions while reducing computational cost. The proposed algorithm, termed the Competitive Parallel Animated Oat Optimization (CPAOO), is evaluated on the CEC 2017 benchmark suite. Experimental results confirm that CPAOO achieves superior performance compared to several state-of-the-art evolutionary algorithms.**

***Index Terms*—Animated Oat Optimization, Competitive Parallel, Communication Strategy, Incentive Mechanism.**

I. Introduction

Optimization problems have traditionally been addressed through mathematical programming methods such as linear programming, integer programming, and gradient-based algorithms [1]. While these classical approaches provide theoretical guarantees for convex problems, they often struggle with non-convex, high-dimensional, or discontinuous search spaces commonly encountered in real-world applications [2]. This limitation has motivated the development of alternative optimization paradigms, particularly Evolutionary Algorithms (EAs).

Unlike traditional methods that rely on mathematical properties like differentiability, EAs operate through population-based stochastic search inspired by biological evolution principles [3], [4]. These algorithms maintain multiple candidate solutions simultaneously and use selection, recombination, and variation operators to explore the solution space. This fundamental difference enables EAs to handle complex problems without requiring gradient information or convexity assumptions, while demonstrating remarkable robustness against local optima. The versatility of EAs has led to their successful deployment across diverse domains including engineering design [5], financial modeling [6], image processing [7], [8], biomedical applications [9], transportation planning [10], feature selection [11], and energy system optimization [12], [13], establishing EAs as indispensable tools in modern computational intelligence [14].

This context has spurred the development of numerous influential EAs, including Grey Wolf Optimizer (GWO) [15], Whale Optimization Algorithm (WOA) [16], Particle Swarm Optimization (PSO) [17], Differential Evolution (DE) [18], and Genetic Algorithm (GA) [19]. As a recent contribution to this field, the Animated Oat Optimization algorithm establishes its search strategy by simulating the dispersal and growth mechanisms of oat seeds in response to environmental factors [20]. In this methodology, each candidate solution is treated as a viable seed, with fitness values quantifying its survival potential. The optimization procedure evolves through three characteristic phases: random diffusion, eccentric motion, and ejection migration. The execution and transition between these phases are governed by humidity variations and physical obstacles within the simulated environment, resulting in distinct search behaviors.

To enhance the performance of EAs in complex optimization tasks, various improvement strategies have been developed in recent years. Among them, surrogate-assisted optimization reduces computational costs by constructing approximate models to replace expensive fitness evaluations [21]. For instance, Yu et al. introduced a surrogate-assisted differential evolution with fitness-independent parameter adaptation (SADE-FI), which utilizes ”dimensional improvements” rather than surrogate-predicted fitness values for parameter adaptation, thereby significantly enhancing performance on high-dimensional expensive problems [22]. Chu et al. developed a surrogate-assisted social learning PSO (SASLPSO) that synergizes a global surrogate, an adaptive local surrogate, and a random grouping-based pre-screening strategy, leading to enhanced performance on expensive optimization prob-

*Corresponding author.

lems, particularly in high-dimensional search spaces [23]. Decomposition-based cooperative coevolution addresses complexity by dividing problems into smaller subproblems, which are then solved by collaborative subpopulations. Zhong et al. proposed a hierarchical Cooperative Coevolution (hCC) framework for Very Large-Scale Traveling Salesman Problems (VLSTSP). This framework begins with small-scale decomposition to manage dimensionality and then systematically re-optimizes subcomponents at higher levels to capture initially missed critical interactions, demonstrating significant potential and scalability [24]. Parallel optimization strategies balance exploration and exploitation through population partitioning and information exchange. For example, Pan et al. developed the Parallel Compact Gannet Optimization Algorithm (PCGOA), which adopts a compact strategy by utilizing a probability distribution model instead of maintaining a full population, thereby significantly reducing memory overhead. The algorithm also incorporates novel communication strategies between subpopulations to improve solution accuracy and convergence speed [25]. In a similar vein, Zhang et al. proposed the Parallel Compact Sine Cosine Algorithm (PC-SCA). This method also leverages a compact strategy through a probability model to virtualize the population, achieving substantial memory savings. Furthermore, it introduces three distinct parallel communication strategies tailored for different problem types (unimodal, multimodal, and complex nonlinear) to effectively escape local optima and enhance solution precision [26].

This paper proposes a cooperative-competitive framework for enhancing the Animated Oat Optimization algorithm, designated as the Competitive Parallel Animated Oat Optimization (CPAOO). The proposed architecture incorporates two innovative communication strategies: the Elite Integration Communication Strategy (EI) and the Elite Orientation Communication Strategy (EO). Initially, the population is partitioned into multiple independent subpopulations that evolve simultaneously using the standard AOO procedure. At predetermined intervals, inter-subpopulation communication is activated through elite individual migration and knowledge sharing, effectively maintaining population diversity while accelerating convergence. The main contributions of this work are summarized as follows:

- The EI Strategy migrates elite individuals from different subpopulations into a designated elite subpopulation, effectively reducing the risk of premature convergence to local optima.
- The EO Strategy enhances both the quality and diversity of individuals across subpopulations, thereby improving the algorithm's global exploration capability.
- A competitive strategy with an incentive mechanism (CIM) is proposed to select high-performing individuals and motivate their active participation in the evolutionary process, effectively reducing computational overhead while improving overall population quality.

The remainder of this paper is organized as follows: Section II outlines the fundamental principles of the original Animated Oat Optimization algorithm. Section III elaborates on the proposed Competitive Parallel Animated Oat Optimization framework. Section IV presents experimental results and performance comparisons using standard benchmark functions. Finally, Section V concludes with summary remarks and potential research directions.

II. Related Work

A. Animated Oat Optimization algorithm

Unlike many EAs that model animal behaviors, AOO uniquely capitalizes on the dynamic interplay between a plant's structural mechanics and its environmental interactions to drive the optimization process. The core inspiration stems from three observed biological phenomena in animated oat seeds: initial random dispersal facilitated by external agents like wind, which promotes exploration; precise locomotion via humidity-driven hygroscopic twisting and rolling of the awn, enabling localized exploitation; and a resilient ejection mechanism where energy stored in the awn is released to overcome obstacles, allowing escape from local optima. These mechanisms collectively equip AOO with a robust strategy for balancing global exploration and local exploitation.

1) Initialization Phase: Similar to most EAs, the AOO algorithm initializes its population by randomly generating N individuals (X_i) within the problem space, defined by the upper bound (U) and lower bound (L). Each individual is initialized as $X_i = r \times (U - L) + L$, where r represents a uniformly distributed random number in the range [0, 1]. The AOO algorithm utilizes several key hyperparameters that are functions of the maximum iteration count (T), the current iteration count (t), and the problem dimensionality (D). These parameters include: seed mass ($m = 0.5 \times \frac{r}{D}$), main awn length ($ML = N \times \frac{r}{D}$), eccentricity coefficient ($e = 0.5 \times \frac{r}{D}$), and dynamic adjustment factor ($c = 1 - \left(\frac{t}{T}\right)^3$).

2) Exploration Phase: In the exploration phase, AOO mimics the random dispersal of seeds under natural forces such as wind. The update rule combines multiple guiding positions to enhance global search capability:

$$W = \frac{c}{\pi} \times (2 \times r_D - 1) \otimes U \tag{1}$$

$$\begin{cases} X_i^{new} = \frac{1}{N} \times \sum_{i=1}^{N} X_i + W & \text{if } mod\left(i, \frac{N}{10}\right) = 0 \\ X_i^{new} = X_{best} + W & \text{if } mod\left(i, \frac{N}{10}\right) = 1 \\ X_i^{new} = X_i + W & \text{others} \end{cases} \tag{2}$$

Here, W denotes the random movement step size, r_D is a D-dimensional random vector with elements in [0, 1], and X_{best} represents the position of the current global best individual.

3) Exploitation Phase: The exploitation phase considers two motion patterns based on whether seeds encounter obstacles:

Eccentric Rolling (No Obstacle): Seeds roll due to the hygroscopic deformation of the awn. The displacement is modeled as:

$$A = U - \left| \frac{U \times t \times \sin(2 \times \pi \times r)}{T} \right| \tag{3}$$

$$R = \left(m \times e + ML^2\right) \times \frac{r_D\left(-A, A\right)}{D} \tag{4}$$

$$X_i^{new} = X_{best} + R + c \times Levy\left(D\right) \otimes X_{best} \tag{5}$$

Ejection (With Obstacle): When a seed hits an obstacle, it stores and releases energy, leading to projectile motion:

$$B = U - \left| \frac{U \times t \times \cos\left(2 \times \pi \times r\right)}{T} \right| \tag{6}$$

$$\begin{array}{ll} k = 0.5 \times (1 + r) & x = 3 \times \frac{r}{D} \\ \theta = \pi \times r & \alpha = \frac{e^{\frac{r^T}{T}}}{\pi} \end{array} \tag{7}$$

$$J = \frac{2 \times k \times x^2 \times \sin\left(2\theta\right)}{mg} \times \frac{r_D\left(-B, B\right)}{D} \times (1 - \alpha) \tag{8}$$

$$X_i^{new} = X_{best} + J + c \times Levy\left(D\right) \otimes X_{best} \tag{9}$$

In the above, R and J represent rolling and ejection displacements, respectively. Parameters such as the elastic coefficient k, awn length variation x, ejection angle θ, and air resistance coefficient α are used to simulate physical motion. The Lévy flight function $Levy\left(D\right)$ helps the algorithm escape local optima. The symbol $r_D\left(-A, A\right)$ denotes a D-dimensional vector with each component randomly drawn from [-A,A], and r^T is a random number in [0,T].

III. Proposed Competitive Parallel Animated Oat Optimization Algorithm

The proposed Competitive Parallel Animated Oat Optimization (CPAOO) algorithm enhances the standard AOO by integrating a parallel co-evolutionary architecture with innovative interaction mechanisms. As illustrated in Fig. 1, the population is initially divided into K subpopulations that evolve independently following the original AOO search procedures. In the figure, IT denotes the predefined iteration threshold that triggers communication, while the evolutionary process within each subpopulation is governed by the Competitive Strategy with an Incentive Mechanism (CIM). Two specialized communication strategies, namely the Elite Integration Communication Strategy (EI) and Elite Orientation Communication Strategy (EO), are periodically activated to facilitate knowledge transfer across subpopulations, effectively balancing global exploration and local refinement. This framework establishes a dynamic information exchange network that addresses the inherent conflict between diversity preservation and convergence speed in traditional single-population evolution.

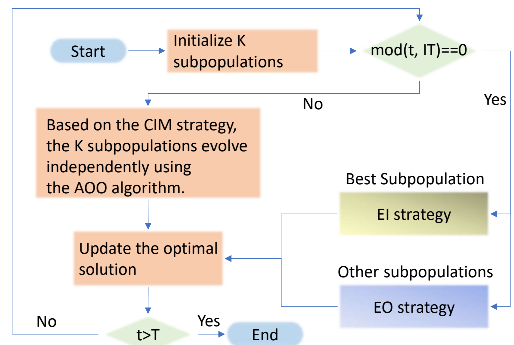


Fig. 1: The Overall Process of CPAOO

A. EI Communication Strategy

The EI strategy operates on a designated best subpopulation, which contains the current global best solution. During communication phases, the top-performing individuals from other subpopulations are identified and migrated into this best subpopulation. To preserve a stable subpopulation size, an equivalent number of lower-fitness individuals are removed from the best subpopulation. This concentration of high-quality solutions not only intensifies the search around promising regions but also effectively prevents premature convergence by ensuring continuous renewal within the best subpopulation. This mechanism mimics the natural phenomenon where superior organisms gather in resource-rich areas, ensuring the algorithm remains focused on promising search directions.

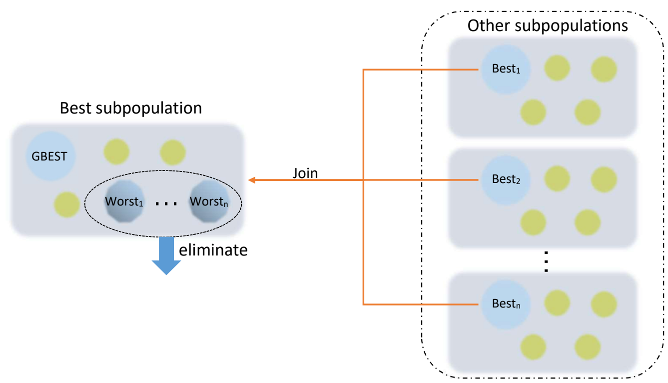


Fig. 2: Elite Integration Communication Strategy

B. EO Communication Strategy

The EO strategy guides the evolution of non-best subpopulations through two complementary operations. First, the global best individual directly replaces the worst member in each non-best subpopulation, enabling direct propagation of elite knowledge. Second, a new guiding solution, X_{new}, is generated by performing a weighted combination of the best individuals from all subpopulations, as defined by:

$$\begin{cases} Q_i = \frac{1}{K-1} \times \left(1 - \frac{f_i}{\sum_{j=1}^{K} f_j}\right) \\ X_{new} = \sum_{i=1}^{K} Q_i \times X_i^{best} \end{cases} \tag{10}$$

Where k denotes the total number of subpopulations, X_i^{best} represents the best individual in the i-th subpopulation, and the weight Q_i is proportional to the fitness value of X_i^{best}. This newly created individual then replaces a randomly selected non-elite member in a different subpopulation, thereby steering the population toward more promising regions for exploration.

This dual guidance mechanism ensures both rapid dissemination of high-quality genes and sustained exploratory vitality across the population.

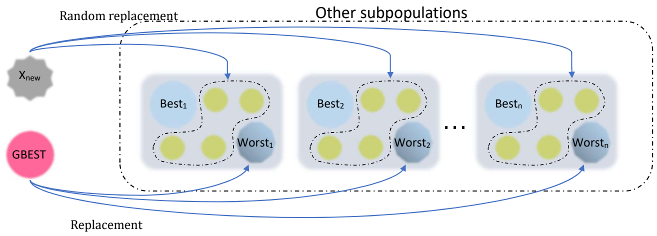


Fig. 3: Elite Orientation Communication Strategy

C. CIM Strategy

To improve computational resource utilization efficiency, this paper introduces CIM strategy. In this strategy, individuals are randomly paired for direct competition. Winners are granted a high probability (e.g., 0.8) of advancing to the next generation, while losers are assigned a lower probability (e.g., 0.2) but are not completely eliminated. This selective pressure continuously enhances population quality throughout iterations while significantly reducing the number of fitness evaluations, thereby effectively lowering computational overhead without compromising solution accuracy. The competition mechanism simulates the survival-of-the-fittest principle in natural selection, ensuring that high-quality individuals receive more evolutionary opportunities while potentially valuable individuals retain their evolutionary possibilities.

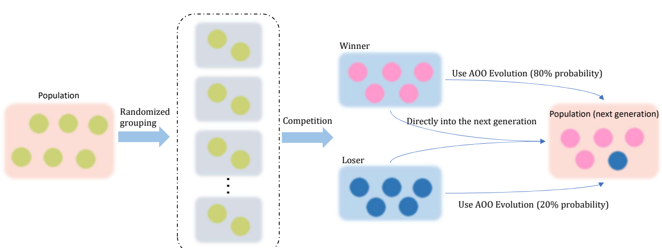


Fig. 4: Competitive Strategy with an Incentive Mechanism

D. Algorithmic Procedure

The complete procedure of CPAOO is summarized in Algorithm 1. The algorithm begins by initializing multiple subpopulations and then iterates through cycles of independent evolution, periodic communication, and competitive selection until termination criteria are met. The synergy between cooperative information exchange and competitive individual selection enables CPAOO to effectively maintain the balance between diversification and intensification throughout the entire search process. By establishing a multi-level interaction mechanism, the algorithm achieves significant improvements in both search efficiency and solution quality.The pseudocode of the CPAOO algorithm is presented below:

Algorithm 1 Competitive Parallel Animated Oat Optimization Algorithm

Input: Number of individuals in the total population (N), fitness function (F), problem dimension (D), number of subpopulations (K), maximum iteration count (T), iteration threshold (IT);
Output: Optimal solution;

```
Initialization: Initialize each subpopulation (G_1–G_K);
while t ≤ T do
    for i = 1 : K do
        Using the CIM strategy, divide individuals into winners (Ws) and losers (Ls);
        Individuals in Ws and Ls evolve using AOO according to the set probability;
    end for
    Update GBEST;
    if mod(t, IT) == 0 then
        Compute X_new using Eq. (10);
        for i = 1 : K do
            if G_i.Best == GBEST then
                Employing the EI strategy for information exchange;
            else
                Employing the EO strategy for information exchange.
            end if
            Update the best and worst individuals in the subpopulation;
        end for
        Update GBEST;
    end if
end while
```

IV. Experiments and Mathematical Analysis

The comprehensive performance of the CPAOO algorithm was evaluated using the CEC 2017 benchmark suite with a problem dimension of 30. This benchmark categorizes functions into four major classes based on their complexity. The competing algorithms selected for this study include classical EAs, novel EAs, and EAs enhanced with parallel strategies. Specifically, the compared algorithms encompass PSO, DE, GWO, PCSCA, and PCGOA. All algorithms were configured according to their original references and implemented in MATLAB R2022b. The experiments employed a population size of 100 and a maximum of 1000 iterations for each run. To ensure statistical reliability, each algorithm was independently executed 20 times, and the average performance was recorded as the final result. For CPAOO, the participation probabilities for individuals in the winner and loser groups were set to 0.8 and 0.2, respectively.

In addition, rigorous statistical analysis was performed on the experimental results to ensure the reliability of the performance comparisons. The non-parametric Wilcoxon rank-sum test was employed to assess the significance of performance

TABLE I: Performance results of various algorithms on CEC2017.

Algorithm / Fun	CPAOO	AOO	GWO	PSO	DE	PCSCA	PCGOA
F1	**2.6922E+03**	3.4317E+03(+)	5.6323E+08(+)	1.4276E+09(+)	6.0705E+03(+)	9.3927E+06(+)	6.9838E+07(+)
F2	8.2157E+03	**3.6048E+02(-)**	3.4665E+04(+)	9.6579E+03(+)	1.2083E+05(+)	5.0708E+04(+)	6.0537E+04(+)
F3	**4.8789E+02**	5.1403E+02(+)	5.7350E+02(+)	6.0193E+02(+)	4.9372E+02(+)	5.4232E+02(+)	5.2732E+02(+)
F4	**5.7243E+02**	6.1701E+02(+)	5.9756E+02(+)	6.9756E+02(+)	6.6078E+02(+)	8.2619E+02(+)	7.9610E+02(+)
F5	6.0076E+02	6.1673E+02(+)	6.0447E+02(+)	6.1829E+02(+)	**6.0000E+02(-)**	6.7523E+02(+)	6.7310E+02(+)
F6	**7.8150E+02**	8.4015E+02(+)	8.5789E+02(+)	9.9892E+02(+)	8.8741E+02(+)	1.1024E+03(+)	1.1138E+03(+)
F7	**8.5343E+02**	8.9527E+02(+)	8.7501E+02(+)	1.0060E+03(+)	9.6551E+02(+)	1.0996E+03(+)	1.0201E+03(+)
F8	**9.0027E+02**	2.4014E+03(+)	1.2922E+03(+)	1.4619E+03(+)	1.0064E+03(+)	1.0445E+04(+)	9.1586E+03(+)
F9	**3.3694E+03**	4.2945E+03(+)	3.6660E+03(+)	7.8584E+03(+)	6.9666E+03(+)	6.3013E+03(+)	5.8399E+03(+)
F10	**1.2355E+03**	1.2422E+03(+)	1.3121E+03(+)	1.4881E+03(+)	1.3169E+03(+)	1.5308E+03(+)	1.5166E+03(+)
F11	**2.4996E+06**	3.6879E+06(+)	3.0948E+07(+)	1.5174E+08(+)	1.3391E+07(+)	4.2780E+07(+)	3.0208E+07(+)
F12	**4.0024E+04**	1.1464E+05(+)	7.9073E+04(+)	5.1645E+07(+)	4.6744E+05(+)	7.4003E+05(+)	4.7324E+05(+)
F13	**7.5540E+03**	1.7788E+04(+)	5.6800E+04(+)	3.0162E+04(+)	1.2055E+05(+)	1.9237E+05(+)	1.5078E+05(+)
F14	**2.0948E+04**	5.4504E+04(+)	2.6015E+05(+)	5.9878E+06(+)	1.0882E+05(+)	1.0128E+05(+)	9.2242E+04(+)
F15	**2.1014E+03**	2.3622E+03(+)	2.4482E+03(+)	3.1940E+03(+)	2.4967E+03(+)	3.4998E+03(+)	3.6120E+03(+)
F16	**1.8453E+03**	2.0195E+03(+)	1.9821E+03(+)	2.1713E+03(+)	1.9631E+03(+)	2.4230E+03(+)	2.4109E+03(+)
F17	**1.7406E+05**	3.4780E+05(+)	6.6857E+05(+)	7.3913E+05(+)	1.0168E+06(+)	4.4144E+06(+)	2.4393E+06(+)
F18	**6.7534E+04**	1.7648E+05(+)	2.3897E+05(+)	1.1190E+07(+)	8.6543E+04(+)	8.6134E+06(+)	6.8694E+06(+)
F19	**2.2118E+03**	2.3752E+03(+)	2.3281E+03(+)	2.5320E+03(+)	2.2799E+03(+)	2.7391E+03(+)	2.8028E+03(+)
F20	**2.3531E+03**	2.3959E+03(+)	2.3747E+03(+)	2.4839E+03(+)	2.4560E+03(+)	2.5889E+03(+)	2.6107E+03(+)
F21	**2.3006E+03**	4.1364E+03(+)	4.3967E+03(+)	6.3471E+03(+)	3.8818E+03(+)	6.7828E+03(+)	5.6628E+03(+)
F22	**2.7027E+03**	2.7543E+03(+)	2.7335E+03(+)	2.8547E+03(+)	2.8046E+03(+)	3.0838E+03(+)	3.0506E+03(+)
F23	**2.8689E+03**	2.9347E+03(+)	2.9253E+03(+)	3.0107E+03(+)	3.0022E+03(+)	3.2150E+03(+)	3.1833E+03(+)
F24	**2.8952E+03**	2.8946E+03(=)	2.9512E+03(+)	2.9976E+03(+)	**2.8877E+03(-)**	2.9460E+03(+)	2.9667E+03(+)
F25	**3.6655E+03**	4.6581E+03(+)	4.3536E+03(+)	4.3555E+03(+)	5.2297E+03(+)	6.7349E+03(+)	4.5214E+03(+)
F26	**3.2171E+03**	3.2379E+03(+)	3.2394E+03(+)	3.2571E+03(+)	3.2180E+03(=)	3.4055E+03(+)	3.3169E+03(+)
F27	**3.1992E+03**	3.2423E+03(+)	3.3835E+03(+)	3.3478E+03(+)	3.2567E+03(+)	3.3167E+03(+)	3.3102E+03(+)
F28	**3.4785E+03**	3.7909E+03(+)	3.6997E+03(+)	4.0857E+03(+)	3.8220E+03(+)	4.8939E+03(+)	4.8822E+03(+)
F29	9.2010E+05	1.3278E+06(+)	6.5275E+06(+)	1.4668E+07(+)	**8.5251E+04(-)**	1.6537E+07(+)	1.8423E+07(+)
+/=/-	-/-/-	27/1/1	29/0/0	29/0/0	25/1/3	29/0/0	29/0/0

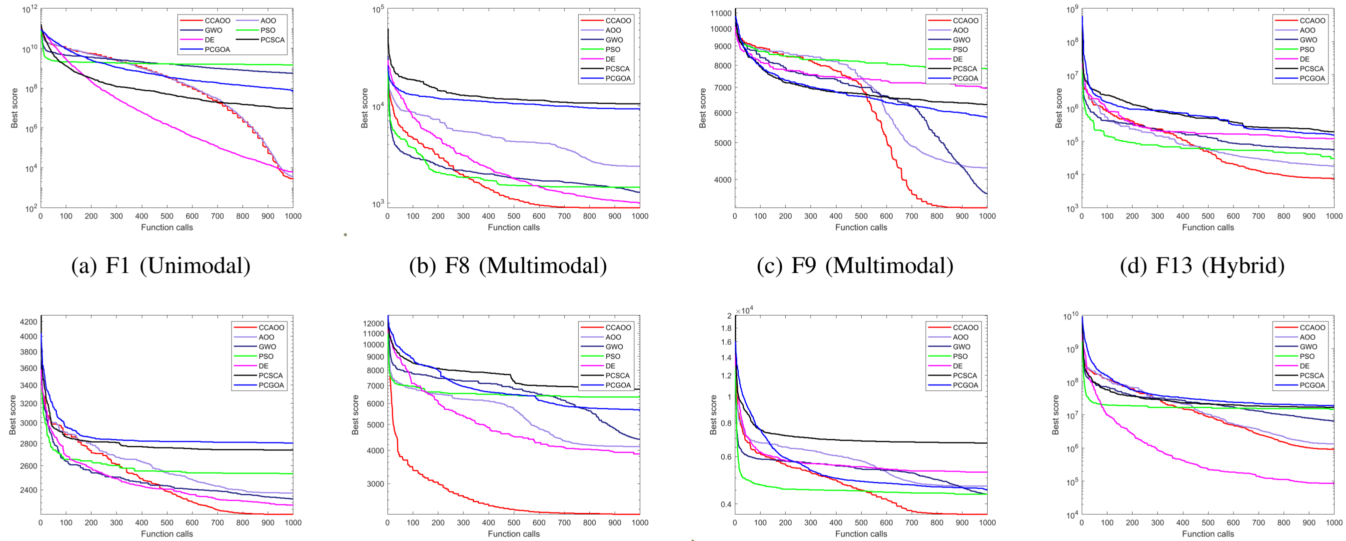
differences between algorithms, while the Friedman test with corresponding post-hoc analysis was conducted to evaluate the overall ranking significance across multiple algorithms.

Table I presents the experimental results of the CPAOO algorithm and the selected competitors on the CEC 2017 benchmark. Compared to other parallel algorithms, CPAOO demonstrates significant advantages. Notably, CPAOO consistently outperformed the other parallel algorithms, PCSCA and PCGOA, across all benchmark functions. Against the original AOO algorithm, CPAOO showed slightly weaker performance only on function F2. Nonetheless, even on F2, CPAOO still surpassed all other competing algorithms. When compared to novel EAs, CPAOO achieved comprehensive superiority across all benchmark functions. In comparisons with classical EAs (specifically PSO and DE), CPAOO demonstrated markedly superior overall performance relative to PSO and outperformed DE on the vast majority of functions. A comprehensive analysis of the experimental data confirms that CPAOO possesses outstanding overall performance.

Table II presents the Friedman test results, where CPAOO achieved the best average rank of 1.1724. Fig. 5 illustrates the convergence behavior of the algorithms on selected benchmark functions. On unimodal functions, CPAOO, despite a slower initial convergence, maintains a stable convergence trend and ultimately attains the best results, showing potential for further improvement. This robust performance is attributed to the EI strategy, which enhances the algorithm's exploitation capability. For complex functions, CPAOO demonstrates superior exploration capability, which is intuitively reflected in its consistent attainment of better solutions. This advantage is particularly evident on function F21. On multimodal functions, CPAOO exhibits a characteristic stepwise convergence pattern. This indicates that the integration of parallel and competitive strategies effectively enables the algorithm to escape local optima. However, CPAOO did not achieve the optimal result on function F29, suggesting there is room for further enhancement in addressing specific complex composition problems.

TABLE II: Friedman test results.

Algorithm	**rank**
CPAOO	1.1724
AOO	2.8276
GWO	3.4828
PSO	5.3448
DE	3.4483
PCSCA	6.1379
PCGOA	5.5862
p:	6.7530E-23



(a) F1 (Unimodal) (b) F8 (Multimodal) (c) F9 (Multimodal) (d) F13 (Hybrid)

(e) F19 (Hybrid) (f) F21 (Composition) (g) F25 (Composition) (h) F29 (Composition)

Fig. 5: Convergence curves of various algorithms on CEC2017 benchmark functions.

V. Conclusion and Outlook

This paper introduces a significant enhancement to the AOO algorithm by proposing the Competitive Parallel AOO algorithm. This is achieved through the integration of a parallel architecture with two novel subpopulation communication mechanisms: the EI and EO strategies. This integration significantly enhances information exchange across subpopulations and effectively balances the algorithm's exploration and exploitation capabilities. Furthermore, the introduction of a competitive strategy with an incentive mechanism enhances population diversity and vitality, while simultaneously reducing the total number of required fitness evaluations, thereby lowering computational overhead. The comprehensive performance and robustness of the proposed CPAOO algorithm have been rigorously validated through extensive experiments on the CEC 2017 benchmark suite. Future research will focus on two primary directions: further refinement of the subpopulation interaction mechanisms to enhance performance on specific problem types, and the application of the CPAOO algorithm to practical domains such as reversible data hiding, to validate its utility in real-world scenarios.

References

[1] S. M. A. Altbawi, S. B. A. Khalid, A. S. B. Mokhtar, H. Shareef, N. Husain, A. Yahya, S. A. Haider, L. Moin, and R. H. Alsisi, "An improved gradient-based optimization algorithm for solving complex optimization problems," *Processes*, vol. 11, no. 2, p. 498, 2023.

[2] P. A. Vikhar, "Evolutionary algorithms: A critical review and its future prospects," in *2016 International conference on global trends in signal processing, information computing and communication (ICGTSPICC)*. IEEE, 2016, pp. 261–265.

[3] E. H. Houssein, M. K. Saeed, G. Hu, and M. M. Al-Sayed, "Metaheuristics for solving global and engineering optimization problems: review, applications, open issues and challenges," *Archives of computational methods in engineering*, vol. 31, no. 8, pp. 4485–4519, 2024.

[4] C.-X. Su, "Piecewise mapping and partitioned search multi-objective firefly algorithm for optimal reservoir scheduling," *Journal of Network Intelligence*, vol. 9, no. 4, pp. 2438–2456, Nov. 2024, november.

[5] A. Younis and Z. Dong, "Adaptive surrogate assisted multi-objective optimization approach for highly nonlinear and complex engineering design problems," *Applied Soft Computing*, vol. 150, p. 111065, 2024.

[6] K. Michalak, "Evolutionary algorithm with a regression model for multiobjective minimization of systemic risk in financial systems," *Soft Computing*, vol. 28, no. 5, pp. 3921–3939, 2024.

[7] S. Chakraborty, A. K. Saha, A. E. Ezugwu, J. O. Agushaka, R. A. Zitar, and L. Abualigah, "Differential evolution and its applications in image processing problems: a comprehensive review," *Archives of computational methods in engineering*, vol. 30, no. 2, pp. 985–1040, 2023.

[8] D.-T. Pham and D.-T.-T. Hoang, "An improved whale optimization algorithm for optimal multi-threshold image segmentation." *J. Inf. Hiding Multim. Signal Process.*, vol. 14, no. 2, pp. 1–11, 2023.

[9] I. A. Pindoo and S. K. Sinha, "Increased sensitivity of biosensors using evolutionary algorithm for bio-medical applications," *Radioelectronics and Communications Systems*, vol. 63, no. 6, pp. 308–318, 2020.

[10] F. Miguel, M. Frutos, F. Tohmé, and M. M. Babey, "A decision support tool for urban freight transport planning based on a multi-objective evolutionary algorithm," *IEEE Access*, vol. 7, pp. 156 707–156 721, 2019.

[11] T.-G. Ngo, H. Nguyen-Cong, T.-T.-T. Nguyen, and T.-K. Dao, "Optimal parameter-feature selection using binary pso for enhanced classification performance." *J. Inf. Hiding Multim. Signal Process.*, vol. 14, no. 4, pp. 172–183, 2023.

[12] A. Izadi, M. Shahafve, and P. Ahmadi, "Neural network genetic algorithm optimization of a transient hybrid renewable energy system with solar/wind and hydrogen storage system for zero energy buildings at various climate conditions," *Energy Conversion and Management*, vol. 260, p. 115593, 2022.

[13] X.-Y. Huang, Q. Liang, X.-F. Chen, and C.-T. Zhan, "Reactive power optimization of ac-dc hybrid system based on improved whale algorithm," *J. Netwwork Intell*, vol. 9, pp. 101–104, 2024.

[14] T.-K. Dao, T.-T. Nguyen, T.-D. Nguyen, T.-X.-H. Nguyen, and T.-T. Nguyen, "A review of the tabu search algorithm for industrial applications." *J. Inf. Hiding Multim. Signal Process.*, vol. 15, no. 3, pp. 179–191, 2024.

[15] S. N. Makhadmeh, M. A. Al-Betar, I. A. Doush, M. A. Awadallah, S. Kassaymeh, S. Mirjalili, and R. A. Zitar, "Recent advances in grey wolf optimizer, its versions and applications," *Ieee Access*, vol. 12, pp. 22 991–23 028, 2023.

[16] M. H. Nadimi-Shahraki, H. Zamani, Z. Asghari Varzaneh, and S. Mirjalili, "A systematic review of the whale optimization algorithm: theoretical foundation, improvements, and hybridizations," *Archives of Computational Methods in Engineering*, vol. 30, no. 7, pp. 4113–4159, 2023.

[17] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle swarm optimization: A comprehensive survey," *Ieee Access*, vol. 10, pp. 10 031–10 061, 2022.

[18] M. Pant, H. Zaheer, L. Garcia-Hernandez, A. Abraham *et al.*, "Differential evolution: A review of more than two decades of research," *Engineering Applications of Artificial Intelligence*, vol. 90, p. 103479, 2020.

[19] S. Katoch, S. S. Chauhan, and V. Kumar, "A review on genetic algorithm: past, present, and future," *Multimedia tools and applications*, vol. 80, no. 5, pp. 8091–8126, 2021.

[20] R.-B. Wang, R.-B. Hu, F.-D. Geng, L. Xu, S.-C. Chu, J.-S. Pan, Z.-Y. Meng, and S. Mirjalili, "The animated oat optimization algorithm: A nature-inspired metaheuristic for engineering optimization and a case study on wireless sensor networks," *Knowledge-Based Systems*, p. 113589, 2025.

[21] H.-Z. Liu, Y. Li, Z.-G. You, J.-Q. Ming, and A. Liu, "Hydroelectric generator excitation control based on improved genetic and rbf neural network," *Journal of Network Intelligence*, vol. 9, no. 4, pp. 2016–2031, Nov. 2024, november.

[22] L. Yu, C. Ren, and Z. Meng, "A surrogate-assisted differential evolution with fitness-independent parameter adaptation for high-dimensional expensive optimization," *Information Sciences*, vol. 662, p. 120246, 2024.

[23] S.-C. Chu, X. Yuan, J.-S. Pan, B.-S. Lin, and Z.-J. Lee, "A multi-strategy surrogate-assisted social learning particle swarm optimization for expensive optimization and applications," *Applied Soft Computing*, vol. 162, p. 111876, 2024.

[24] R. Zhong, E. Zhang, and M. Munetomo, "A hierarchical cooperative coevolutionary approach to solve very large-scale traveling salesman problem," in *International Conference on Optimization and Learning*. Springer, 2023, pp. 74–84.

[25] J.-S. Pan, B. Sun, S.-C. Chu, M. Zhu, and C.-S. Shieh, "A parallel compact gannet optimization algorithm for solving engineering optimization problems," *Mathematics*, vol. 11, no. 2, p. 439, 2023.

[26] S. Zhang, F. Fan, W. Li, S.-C. Chu, and J.-S. Pan, "A parallel compact sine cosine algorithm for tdoa localization of wireless sensor network," *Telecommunication Systems*, vol. 78, no. 2, pp. 213–223, 2021.