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A power optimization approach for Mixed Polarity Reed_Muller logic circuits based on multi-strategy fusion memetic algorithm*

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Abstract: The power optimization of Mixed Polarity Reed-Muller (MPRM) logic circuits is a classic combinatorial optimization problem. Existing approaches often suffer from slow convergence and a propensity to converge to local optima, limiting their effectiveness in achieving optimal power efficiency. Firstly, we propose a novel Multi-strategy Fusion Memetic Algorithm (MFMA). MFMA integrates global exploration via the Chimp Optimization Algorithm with local exploration using the Coati Optimization Algorithm based on the Optimal position Learning and Adaptive weight factor, complemented by population management through truncated selection. Leveraging MFMA, we propose a power optimization approach for MPRM logic circuits that searches for the best polarity configuration to minimize circuit power. Experimental results based on Microelectronics Center of North Carolina (MCNC) benchmark circuits demonstrate significant improvements over existing power optimization approaches. MFMA achieves a maximum power saving rate of 72.30% and an average optimization rate of 36.21%; the search solutions are faster and of higher quality, validating the effectiveness and superiority of MFMA.

Key words: Power optimization; Multi-strategy fusion memetic algorithm; Mixed Polarity Reed-Muller; Combinatorial optimization problem

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1 Introduction

As the Integrated Circuit (IC) industry rapidly evolves alongside advancements in electronic information technology, the significance of IC in digital systems, computer manufacturing, communication equipment, and various other domains continues to grow (Huan et al., 2021). However, with this rapid progress comes a notable issue: the escalating power of IC. This increase not only poses challenges for portable devices, causing power difficulties and chip overheating, but also impacts the cost of heat dissipation and packaging. Consequently, optimizing chip power has emerged as a pivotal factor in IC design and optimization.

Digital logic circuits can be implemented using either Boolean logic circuits, which rely on AND/OR/NOT operations, or Reed-Muller (RM) logic circuits, which utilize XNOR/OR or XOR/AND operations. Numerous studies have in-

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dicated that for certain circuits (Zhao GC et al., 2024), RM logic circuits offer more significant advantages over Boolean logic circuits in terms of power, area efficiency, reliability, and testability. Consequently, RM logic circuits have garnered considerable attention as a research focus in the field of integrated circuit design and optimization (Lopera et al., 2021). The most prevalent forms of RM logic circuits are the XNOR/OR-based Mixed Polarity RM (MPRM) logic circuits and the XOR/AND-based Fixed Polarity RM (FPRM) logic circuits. For any n-variable Boolean logic circuit, there exist 3^n different mixed polarities and 2^n different fixed polarities. As a result, MPRM logic circuits provide a large optimization space and potential for improved performance compared to FPRM logic. Furthermore, varying input variables yield different circuit expressions, corresponding to distinct polarities (Liu et al., 2024). Optimizing power in MPRM circuits involves identifying the optimal polarity configuration that minimizes power, thus posing a typical combinatorial optimization problem.

In MPRM logic circuits, the exhaustive search method effectively finds the optimal polarity for circuits with fewer input variables. However, as the number of input variables increases, the optimization space grows exponentially, making exhaustive methods time-consuming and inefficient, ultimately failing to yield optimal solutions within a reasonable timeframe. Due to their simple structure, fast search capabilities, and resistance to local optima, swarm intelligence optimization algorithms have found widespread application in MPRM circuit optimization. Zhou et al. (2022) propose an optimizer that includes global exploration and local depth exploitation and utilizes a Huffman tree construction algorithm to seek the minimum power consumption FPRM circuit, although its optimization efficiency is lower when dealing with large-scale circuits. Wang X et al. (2015) proposed an improved adaptive genetic algorithm (IAGA) to optimize the best polarity traversal sequence for MPRM logic circuits, accelerating the polarity optimization speed, but a comparison with other classical swarm intelligence algorithms is lacking. Similarly, He et al. (2024) proposed a whale optimization algorithm (TMWOA), which employs a dual-population strategy and mutation strategy, enhancing convergence speed and enabling escape from local optima through information exchange, but low efficiency in large-scale optimization problems is still demonstrated. Existing MPRM logic circuit power optimization methods based on traditional swarm intelligence algorithms face challenges of slow convergence and susceptibility to local optima (Khatana et al., 2024).

In this paper, we propose a power optimization approach for MPRM logic circuits based on multi-strategy fusion memetic algorithm. Compared to existing power optimization approaches, our main contributions are as follows:

(1) A Multi-strategy Fusion Memetic Algorithm (MFMA) is proposed. It comparises a global exploitation optimizer utilizing the Chimp Optimization Algorithm (ChOA), a local exploration optimizer based on the Coati Optimization Algorithm with an Optimal position Learning and Adaptive weight factor (COA-OLA), and a population selection optimizer employing a truncated selection algorithm. The MFMA expedites convergence, enhances search accuracy, and prevents the algorithm from succumbing to local optima.

(2) A power optimization approach for MPRM logic circuits is introduced, employing the MFMA to search the optimal polarity configuration with minimal power. Notably, this paper marks the pioneering application of the ChOA and COA to RM logic circuit optimization, enhancing the search capabilities and solution quality in this domain. As far as we know, this is the first attempt to apply a memetic algorithm to optimize the power of RM circuits.

(3) The experimental results, conducted on power using the MCNC benchmark circuit, serve to validate the efficacy and superiority of the proposed power optimization approach.

2 Power estimation model

Currently, the most prevalent form of integrated circuits is CMOS circuits. Compared to dual-gate and transmission gate logic, CMOS exhibits a stronger capability for driving loads and does not require additional logic levels, thereby simplifying the design and testing of power circuit (Li et al., 2024). Additionally, the CMOS structure offers benefits such as full-swing output voltage and a symmetrical layout. However, a significant portion of the power in chips arises from dynamic power due to the charging and discharging of load capacitance Ju et al. (2024) the switching activity rate of the gate circuit can typically be derived from its output signal probability:

$$E_{\mathrm{swd}}^{i} = 2P(g), \tag{1}$$

$$E_{\mathrm{swd}}^{i} = 2P(g)\big(1-P(g)\big), \tag{2}$$

where $P(g)$ represents the signal probability of the output, which can be obtained by combining the input signal probability with the signal chance transfer algorithm. The power of digital integrated circuits is primarily divided into two parts: (1) Dynamic power, which arises from capacitor charging and discharging during signal transitions and can be calculated using Eq. (8). Within dynamic power, switching power is the predominant factor, while short-circuit power-resulting from a brief short between the input and output-has a relatively minor impact; (2) Static power, which refers to the power consumed when the circuit is in a static state and not switching. This component is independent of input signals and depends solely on circuit design and operating conditions, calculable using Eq. (9). Static power typically accounts for less than 1% of total power, significantly lower than dynamic power. Therefore, this paper focuses on calculating switching activity in dynamic logic. From Eq. (1), the MPRM circuit expression is composed of multi-input XNOR and OR operations, with power primarily arising from these components. Multi-input logic operations must be decomposed into two-input operations to calculate the power of the MPRM circuit. Consequently, its power is determined by the two-input XNOR and OR gates, as shown in Eqs. (3) and (4).

$$\Pr(g) = 1 + 2\cdot\Pr(x) + \Pr(y) - \Pr(x)\cdot\Pr(y), \tag{3}$$

$$\Pr(f) = \Pr(x) + \Pr(y) - \Pr(x)\cdot\Pr(y). \tag{4}$$

Meanwhile, the multi-input XNOR term and multi-input OR term need to be decomposed into a series of two-input XNOR terms and two-input OR terms. The decomposition algorithms are detailed in the literature by Qin et al. (2023), and the signal probabilities obtained by employing different decomposition algorithms will vary, as illustrated in Figs. 1 and 2:

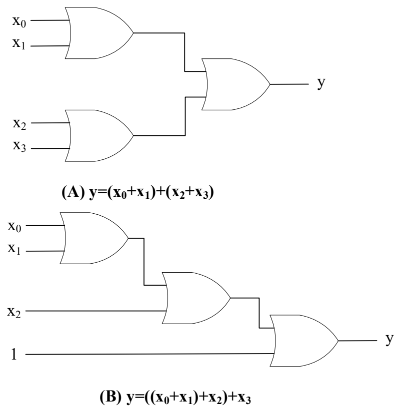

Fig. 1 OR gate decomposition approach: (A) $y=(x_0+x_1)+(x_2+x_3)$, and (B) $y=((x_0+x_1)+x_2)+x_3$

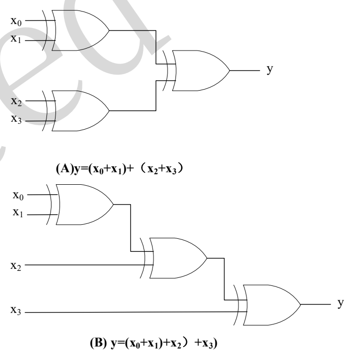

Fig. 2 XNOR gate decomposition approach：(A) $y=(x_0+x_1)+(x_2+x_3)$, and (B) $y=((x_0+x_1)+x_2)+x_3$

3 Multi-strategy fusion memetic algorithm

The memetic algorithm was first proposed by Pablo Moscato in 1989 (Moscato, 1989), based on the concept of simulating cultural evolution for optimization purposes. Essentially, it combines a population-based global search with an individual-based local search. Since its inception, the Memetic Algorithm has gained popularity among researcher due to its ability to overcome the limitations of the Genetic Algorithm (GA) and achieve superior optimization capabilities. It has been successfully applied in various fields. The Memetic Algorithm adapts to various problem environments by exploring diverse solutions. It effectively reduces the search space and quickly converges to optimal or near-optimal solutions, thus enhancing the efficiency of MPRM logic circuits design. Additionally, the algorithm's flexibility allows it to better accommodate the specific constraints and requirements of MPRM logic circuits, improving power optimization efficiency. To address these challenges, we propose a Multi-strategy Fusion memetic Algorithm (MFMA).

MFMA comprises three main components: a global exploitation optimizer employing the ChOA, a local exploration optimizer utilizing the Coati Optimization Algorithm based on optimal position learning and adaptive weighting factor, and a population selection optimizer employing a truncated selection algorithm. MFMA integrates these strategies to efficiently traverse the search space, balancing global exploration with local exploitation and selecting promising individuals for further exploration. Through this holistic approach, MFMA aims to overcome the limitations of existing methods and facilitate the discovery of more effective power-optimized solutions for MPRM logic circuits. The details of the algorithm are described as follows.

Khishe and Mosavi (2020) proposed the ChOA a novel meta-heuristic algorithm that simulates the behaviors of chimpanzee groups in attacking, driving away, obstructing, and pursuing prey. Due to its strong global search capabilities and ease of implementation, it is suitable for various optimization problems. Therefore, ChOA is selected as the global optimization algorithm to enhance convergence speed. However, in optimizing the power consumption of MPRM logic circuits, it may fall into local optima and consume substantial computational resources. To address this, a local search algorithm can be proposed to balance exploration and exploitation, thereby improving solution quality. The Coati Optimization Algorithm (COA) (Dehghani et al., 2023), inspired by coati behavior, demonstrates strong adaptability and robustness, allowing for extensive exploration of the search space and improved search efficiency. Thus, utilizing COA as the local optimization algorithm can effectively resolve issues related to local optima and resource consumption.

3.1 Coati Optimization Algorithm based on optimal position learning and adaptive weight factors

Compared to other swarm intelligence algorithms, the COA has fewer parameters, a clear division of labor among individuals, is easy to implement, and exhibits high stability. However, it is prone to getting stuck in local optima during iterations and has a slower convergence rate (Hasanien et al., 2023). In the first stage of prey hunting, some raccoons climb trees to scare the iguana until it falls, while those on the ground prepare to hunt. If the location where the iguana lands is considered the optimal position within the population, its landing spot may be chosen randomly, introducing randomness that could lead the algorithm to a local optimum. In the second stage, when escaping from predators, a raccoon changes its position randomly to evade attacks. However, this strategy can result in stagnation, as it may not effectively search for more optimal solution (Suau and Zegard, 2023). To address these shortcomings, this paper proposes a coati optimization algorithm based on optimal position learning and adaptive weight factor (COA-OLA). This method enhances the algorithm's search accuracy and helps avoid local optima by refining the landing position of the iguana and adjusting the coati's escape strategy.

3.1.1 Optimal position Learning

Due to the random selection of prey positions in the initial phase of the original algorithm, the search accuracy is relatively poor. Inspired by literature Yıldız et al. (2023), this paper proposes an optimal position learning strategy. This strategy calculates the fitness values of the remaining coati individuals and updates the prey position by combining the best fitness individual with two randomly selected individuals. This approach enables the raccoon individuals to approach the prey more quickly and enhances their attack efficiency, thereby improving the algorithm's search speed. The mathematical model is as follows:

$$\begin{aligned}\text{Iguana}^{G}: \text{Iguana}_{j}^{G} &= x_{i,j}^{1} + R_{d*}(x_{i,j}^{1} - x_{i,j}^{2}) \\ &\quad + (x_{i,j}^{3} - \text{Iguana}_{j}^{G}) \qquad (5)\end{aligned}$$

$i = 1, 2..., N_2$, j=1,2,...,m,

where $x_{i,j}^{1}$ denotes the location of the optimal individual obtained through the computation of fitness values, and $x_{i,j}^{2}$ and $x_{i,j}^{3}$ denote two individuals randomly selected from the remaining coati population on the ground, respectively. R_d denotes the random number within the interval (1, d) dimension.

3.1.2 Adaptive weighting factor

In the original algorithm's stage of escaping from predators, coati individuals randomly select a position nearby to flee. This random escape does not effectively cover the entire search space and fails to guide the raccoons to explore significantly different areas, making it difficult to balance exploration and exploitation. As a result, the algorithm is prone to stagnation in local optima. Inspired by Wang WC et al. (2023), this paper proposes an adaptive weight factor strategy. By adjusting the inertia weight, raccoon individuals can choose new positions based on the distance from the predator, thereby enhancing the algorithm's local search capability. The mathematical model for this strategy is as follows:

$$w = \sin\left(\frac{\pi * i}{2 * N_2} + \pi\right) + 1, \qquad (6)$$

$$X_I^{P_2}: x_{i,j}^{P_2} = w * x_{i,j}^4 + (r * r * x_{i,j}^5 - x_{i,j}^6) \qquad (7)$$
$$i = 1, 2..., N_2, \ \text{j=1,2,...,m},$$

where w denotes the weighting factor, $X_I^{P_2}$ represents the new position obtained by the individual coati after escaping from the predator， $x_{i,j}^4$ denotes the location information of the optimal coati individual calculated by the fitness value, while $x_{i,j}^5$ and $x_{i,j}^6$ denote the location information corresponding to two randomly selected coati individuals from the coati population, respectively. The algorithm's corresponding flow is depicted below:

Algorithm 1 COA-OLA

Input: Evolutionary parameters
Output: Optimal solution
Initialize the population
for t=1: Max_iteration **do**
Update position of the iguana
Update the position of the top one-half of individuals in the population with Eq. (18) and Optimal position Learning
Update the position of individuals in the posterior one-half of the population with Eq. (20)
for i=1: N_2 **do**
Update population individual positions with Adaptive weight factor strategies
End for
Retention of optimal individuals of the population
End for
Output: optimal solution

3.2 New stock selection approach

During the algorithm's iterative process, a high-quality population can achieve an even distribution of individuals and increase diversity (Zhao BW et al., 2024). After mixing the new population obtained from local search with the original population, it is necessary to reselect individuals with better fitness to ensure natural selection (Suau and Zegard, 2023). This selection is based on individual fitness evaluations, and commonly used selection operators include tournament selection, random sampling, linear ranking selection, Monte Carlo selection, and truncation selection. Experiments in this paper demonstrate that using truncated selection can effectively improve population quality and accelerate the algorithm's convergence speed (Yin et al., 2024).

In truncation selection, the fitness values of the population are first calculated and sorted from best to worst, allowing only a fixed number of individuals to advance to the next iteration. The initial population N_1 is generated using a global optimization algorithm, and a local search algorithm subsequently optimizes it to create a new population N_2. After merging and sorting the two populations, the top N_1 individuals with better fitness are selected for further iterations. This selection process is illustrated in Fig. 3.

Based on the preceding sections, the pseudo-code for MFMA is outlined in Algorithm 3.

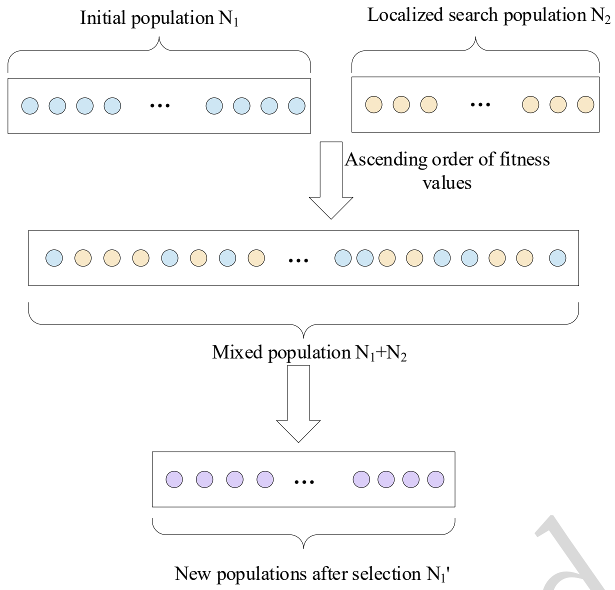

Fig. 3 Truncation of the selection process

Algorithm 2 MFMA

Input: Evolutionary parameters
Output: Optimal solution
Initialize the chimp population N_1
Update the position of each chimp
for l=1: Max_iteration **do**
Obtain information on the top four optimal chimp individuals
Initialize the coati population N_2
for t=1: Max_iteration **do**
Update position of the iguana
Update the position of the top one-half of individuals in the population with Eq. (18) and Optimal position Learning
Update the position of individuals in the posterior one-half of the population with Eq. (20)
for i=1: N_2 **do**
Update population individual positions with Adaptive weight factor strategies
End for
Retention of optimal individuals of the population
End for
Using truncation selection to obtain new populations
Update new top four optimal individuals
End for
Output: optimal solution

4 Power optimization of MPRM logic circuits

Power optimization of MPRM logic circuits constitutes a classic combinatorial optimization challenge, with existing approaches often prone to issue such as susceptibility to local optima and slow convergence rates. Leveraging the power model introduced earlier, MFMA is employed to optimize the power of MPRM logic circuits, seeking the polarity configuration that minimizes circuit power. The implementation steps are outlined below:

Algorithm 3 MPRM logic circuits power optimization

Input: Boolean circuit with *n* variables. Evolutionary parameters
Output: Optimal polarity corresponding to the MPRM logic expression that minimizes power consumption
initialize MFMA Required Parameters
initialize the individual position and calculate the corresponding fitness value E_{swd}^{i}
for *l*=1: Max_iteration **do**
obtain information on the top four optimal chimp individuals
for *t*=1: Max_iteration **do**
initialize the raccoon individual position, iguana individual position, and calculate the corresponding fitness value *E*
execution of the attacking prey phase with individual position updating using an optimal position learning strategy
execute the Escape from Predator phase to escape from predators using a weighting factor strategy
end for
using Truncated Selection Strategies for Population Renewal
calculate the value of individual fitness of the population *E*
update new top four optimal individuals
end for
output: Optimal polarity corresponding to the MPRM logic expression that minimizes power

5 Experimental results and analysis

Utilizing Matlab R2020b for code implementation, the software operates on a Windows 10- based system, equipped with an Intel Core i7-10700 CPU, 32 GB RAM. The test circuit selected is the MCNC Benchmark circuit. Performance validation of swarm intelligence optimization algorithms revolves around three key aspects: convergence speed, algorithm performance, and generalizability. Therefore, this paper conducts ablation experiments, power optimization of MPRM logic circuits, and tests on the IEEE CEC test set to validate the proposed algorithm's performance across these dimensions. Given the stochastic nature of the swarm intelligence optimization algorithm, experimental results are averaged over ten runs for each test set to ensure robustness. Additionally, it is important to consider the operating environment, parameters, and evaluation metrics of different swarm intelligence optimization algorithms. To ensure the fairness of the experiment, all parameters required for the algorithm were determined through an orthogonal experiment. The results are shown in Table 1. In this table, Level Test refers to the experimental group, N_2 represents the number of individuals in the raccoon population, N_1 indicates the number of individuals in the chimpanzee population, and T denotes the maximum number of iterations for the algorithm. Furthermore, for the comparison algorithms, all parameter values, except those that are intrinsic to the algorithms, were kept consistent with those of the proposed algorithm. These parameter values are detailed in Table 2.

Table 1 Orthogonal experiment parameters

Level test	N_2	N_1	T	Average
1	26	30	35	769.22
2	26	35	45	776.68
3	26	40	40	759.58
4	28	30	45	770.47
5	28	35	40	737.27
6	28	40	35	778.21
7	30	30	40	782.99
8	30	35	35	764.89
9	30	40	45	774.34

Table 2 Experimental data for test set

	MFMA	ALO	PSO	WOA	COA	ChOA	A-MFMA	B-MFMA
Population size	35	35	35	35	35	35	35	35
Iteration number	1000	1000	1000	1000	1000	1000	1000	1000
Number of cycles run	10	10	10	10	10	10	10	10

5.1 Ablation experiment

Characterized by fewer parameters and a faster optimization search speed, ChOA exhibits notable features. However, when confronted with large-scale optimization problems, it is prone to issues such as falling into local optimum and slow convergence speed. To validate the performance of each of the innovations, the new algorithm obtained by sequentially incorporating each innovation is compared with the original ChOA on the IEEE CEC test set. The experimental results are presented in Table 3, where Set denotes the name of the selected test set, Function represents the name of the function randomly selected from the test set, Standard indicates the different evaluation metrics computed based on the experimental results, Ave signifies the average value of each algorithm over ten runs on the different functions, and best denotes the optimal value obtained in the experiment. Additionally, A-MFMA denotes the addition of the local search algorithm COA to the original algorithm, while B-MFMA denotes the addition of the optimal location learning strategy to A-MFMA.

As depicted in Table 3, the new algorithm derived from sequentially integrating each of the innovations consistently outperforms ChOA across different test sets. In addition, based on the experimental averages, MFMA yields superior values, followed by A-MFMA and B-MFMA, with ChOA exhibiting the least favorable outcomes. Regarding the optimal value, determined as the minimum value obtained in the experiment, ChOA yields the largest optimal value. However, all three new algorithms incorporating different innovations demonstrate negligible differences in the optimal value, with MFMA exhibiting a general advantage. Upon analyzing the experimental results, the proposed MFMA demonstrates superior performance, notably in achieving the algorithm's optimal value, underscoring the superiority of the proposed algorithm. The reasons for these experimental outcomes can be broadly categorized into the following three parts:

(1) In scenarios where the search space is excessively large, ChOA may struggle to locate the optimal value within the iterative process. To address this limitation, a new local search algorithm, COA, along with a population selection strategy, is incorporated into the original algorithm, resulting in the development of the new algorithm A-MFMA. This integration effectively narrows down the search space, facilitating the discovery of the algorithm's optimal solution while preserving the elite population. Consequently, A-MFMA demonstrates improved convergence speed compared to its predecessor.

(2) Given that individual position selection in COA predominantly relies on randomness, the localized search process may lead to slow convergence. To address this issue, the new algorithm, MFMA, incorporates the optimal position learning strategy into the local search. This addition integrates optimal positions from the population into individual position selection, thereby expediting convergence speed.

(3) Additionally, in the final escape predator stage of COA, an adaptive weighting strategy is introduced to adjust individual motion steps, facilitating a quicker escape from a local solution. This enhancement aims to prevent the algorithm from being trapped in local optima. Consequently, MFMA exhibits faster search capabilities and attains superior final solutions.

Table 3 Ablation experiment test results

Set	Function	Standard	ChOA	A-MFMA	B-MFMA	MFMA
2019	F3	Ave	10.1527	9.4022	7.5436	7.1943
		Best	5.3731	5.2293	3.2485	4.0357
	F6	Ave	10.8505	10.0401	9.8551	9.7078
		Best	10.1586	8.4792	8.5220	8.3931

	F8	Ave	5.3669	4.9212	4.7368	4.5605
		Best	5.0513	3.8661	4.5148	4.2269
	F9	Ave	1.5225	1.5078	1.4192	1.4077

To be continued

Table 3 (continued)

		Best	1.2841	1.4432	1.2163	1.2949
	F10	Ave	21.4411	21.3696	21.3297	21.3272
		Best	21.3136	21.2078	21.1823	21.1388
2022	F3	Ave	660.4345	644.1511	641.4526	640.2807
		Best	640.0812	630.4283	632.6393	628.2525
	F4	Ave	930.71	891.5244	874.839	903.7881
		Best	911.9187	901.8239	884.5712	882.1141
	F5	Ave	2924.664	2143.449	2046.742	2015.967
		Best	2624.837	1792.98	1742.162	1715.962
	F9	Ave	2764.985	2571.001	2556.346	2539.089
		Best	2617.578	2492.277	2491.055	2488.957
	F10	Ave	6708.998	6282.002	5402.276	3450.28
		Best	5447.077	5374.694	2784.491	2513.652

5.2 Convergence performance

To provide a more intuitive representation of convergence performance, four test functions were randomly selected and plotted based on the experimental results from Algorithm 3. Figs. 4-7 depict these plots. In these figures, the horizontal axis represents the number of iterations, while the vertical axis represents the average value obtained during the iterations. It is evident from the figures that ChOA exhibits the slowest convergence, followed by A-MFMA and B-MFMA, while MFMA demonstrates the fastest convergence with superior results. This disparity can be attributed to the inherent randomness in ChOA's iterative process of position updates, resulting in a wider search space range and making it difficult to find the optimal solution. However, with the incorporation of the local search algorithm and the new population selection strategy, MFMA achieves an accelerated search speed, improved search accuracy, and mitigation against falling into local optima.

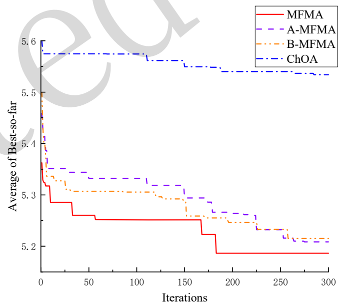

Fig. 4 IEEE CEC 2019-F8

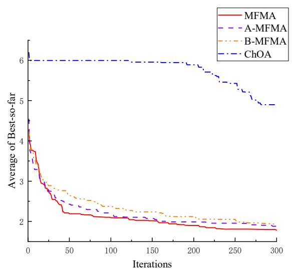

Fig. 5 IEEE CEC 2019-F9

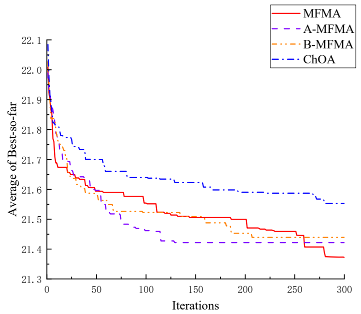

Fig. 6 IEEE CEC 2019-F10

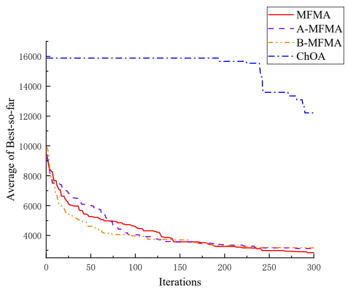

Fig. 7 IEEE CEC 2022-F5

5.3 Power Comparison

To validate the effectiveness of the proposed MFMA for power optimization of MPRM circuits, four algorithm-ChOA, ALO, PSO, and DO are selected for comparison with MFMA. The parameters required for MFMA have been determined through orthogonal experiments. To ensure the fairness of the experiment, the population size of all five algorithms is set to 35, and the termination condition is reaching 2000 evaluations. Twelve circuits are randomly selected from the MCNC test circuits as the experimental circuits. The experimental results are the average of ten runs for each algorithm to mitigate the effect of randomness in swarm intelligence algorithms. As presented in Table 4, "Circuits" denotes the name of the randomly selected circuits from the MCNC test circuits. "Stand" represents the different data compared in the experiments, with "Best" indicating the optimal value obtained in the experiments. The minimum power value obtained in the experiments is considered the optimal value, while Ave signifies the average value obtained by running the algorithm ten times, Std denotes the standard deviation of the results obtained from ten runs of the algorithm. Additionally, Save1 denotes the power saving rate of MFMA compared to ChOA, Save2 represents the power saving rate of MFMA compared to PSO, Save3 indicates the power saving rate of MFMA compared to ALO, and Save4 indicates the power saving rate of MFMA compared to DO. The power saving rate is calculated according to Eq. (8).

$$E_{\text{Save}} = \frac{E_Q - E_M}{E_Q} \times 100\%, \tag{8}$$

where E_{Save} represents the power saving rate obtained by calculating based on the experimental results, E_Q denotes the experimental results of the power of the three compared algorithms, and E_M signifies the experimental results of the power of MFMA.

As shown in Table 4, the circuit power results achieved by MFMA for various circuits surpass those of the other four compared algorithms. Specifically, MFMA yields an average savings of 27.31% in circuit power compared to ChOA, 47.72% compared to PSO, 33.61% compared to ALO, and 25.29% compared to DO. The optimal values indicate that PSO performs the poorest, followed by ChOA and ALO, with DO performing better, while MFMA outperforms all. In both average and standard deviation, MFMA also has the best search results, proving the superiority of the proposed algorithm. The primary reason for these experimental outcomes is the following:

(1) During the pre-iteration process of the algorithm, the initial phase involves a global search conducted by the global exploitation optimizer, which comprises ChOA. This facilitates the rapid identification of the optimal solution within the initial population. Subsequently, the location information of the optimal solution is transmitted to the local search algorithm to expedite the convergence speed of the algorithm.

(2) During the local search algorithm, both the optimal position learning strategy and adaptive weight factor strategy are employed. These strategies facilitate the development of local search around the optimal individual position, thereby enhancing the algorithm's search accuracy and preventing it from falling into local optima.

(3) Following global exploitation and local ex-

ploration, the individual information of the population is selected using a truncated selection algorithm. This process retains the superior individuals from the mixed population for the next iteration, ensuring that the individuals participating in each iteration of the algorithm are the optimal ones.

Table 7 Experimental data on the power of four algorithms

Circuits	Stand	ChOA	PSO	ALO	DO	MFMA	Save1	Save2	Save3	Save4
	Best	622.31	738.60	735.55	281.02	254.29				
Sqrt8	Ave	742.20	826.48	784.38	281.02	259.15	65.08%	68.64%	66.96%	7.78%
	Std	91.14	47.18	45.30	5.9E-14	11.27				
	Best	202.54	224.62	216.77	118.08	71.79				
Prom2	Ave	249.60	293.40	255.26	118.08	85.65	65.68%	70.80%	66.44%	27.46%
	Std	28.35	40.35	23.11	14.60	0				
Ex1010	Best	3720.57	10761.5	6514.23	4027.90	2560.75	38.94%	71.77%	62.15%	24.49%
	Ave	5818.65	12588.4	9385.72	4704.87	3552.47				
	Std	1172.51	834.04	1385.22	498.43	537.22				
	Best	138.03	138.00	135.65	136.18	89.42				
Alu2	Ave	154.17	165.86	141.60	138.06	105.52	31.55%	36.38%	25.48%	23.56%
	Std	14.75	18.72	6.74	0.68	17.89				
	Best	73.00	64.06	63.60	31.93	31.93				
Clpl	Ave	115.29	75.91	69.83	31.93	31.93	72.30%	57.93%	54.27%	0
	Std	35.85	7.39	3.33	0	0				
	Best	248.84	481.70	340.79	302.18	215.26				
Br2	Ave	322.63	968.85	555.46	487.20	304.97	5.47%	68.52%	45.09%	37.40%
	Std	48.49	260.89	138.56	161.27	51.31				
	Best	678.59	893.195	777.22	672.96	350.58				
T3	Ave	847.40	1225.41	931.30	793.21	447.42	47.20%	63.48%	51.95%	43.59%
	Std	113.82	214.48	101.43	84.89	118.65				
	Best	27.27	38.72	30.89	16.03	25.82				
Newalpl1	Ave	33.67	61.86	37.29	43.15	29.26	13.09%	52.69%	21.53%	32.19%
	Std	6.43	19.60	7.22	25.81	2.42				
	Best	137.62	134.60	134.60	128.61	72.48				
Alu1	Ave	169.06	169.32	148.43	128.61	76.01	55.02%	55.10%	48.79%	40.89%
	Std	18.98	21.29	7.83	12.27	0				
	Best	201.54	137.76	152.66	159.70	121.97				
Newapla	Ave	279.34	268.30	223.31	199.67	133.20	52.31%	50.35%	40.35%	33.28%
	Std	47.40	69.32	44.60	23.90	13.42				
	Best	3039.19	4532.91	3681.70	3275.03	1819.23				
Alu4	Ave	4011.68	5417.17	4737.93	3699.00	2560.60	36.17%	52.73%	45.95%	30.77%
	Std	562.39	831.26	473.97	550.97	355.81				
	Best	5982.738	22908.89	14242.54	7962.28	8674.54				
Table3	Ave	12 341.15	31 087.57	21 257.02	12 286.44	11 589.55	6.09%	62.71%	45.47%	5.67%
	Std	2768.97	4376.48	4675.03	3069.66	2419.75				

To be continued

Table 7 (continued)

5.4 Convergence Comparison

To illustrate the performance of the proposed algorithms more intuitively, four circuits from Table 1 are randomly selected. The optimal solution of power obtained by each algorithm during the iteration process is calculated for these circuits. The average value of ten runs of individual circuits for each algorithm is then determined. Convergence curves are plotted using the acquired data, as depicted in Figs. 8-11. In the figures, the horizontal axis represents the average value of power obtained from ten runs of the algorithm. From the figures, it is evident that the proposed MFMA converges the fastest with better optimal solution for power. DO follows as the second-best solution, with ChOA and ALO follow closely behind, while PSO converges the slowest. This disparity can be attributed to the fact that MFMA incorporates COA-OLA as a local optimization algorithm on top of the global optimization algorithm ChOA, a truncated selection algorithm is utilized for population selection to ensure the retention of elite individuals.

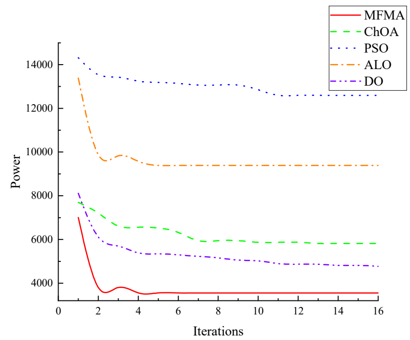

Fig. 8 Ex1010

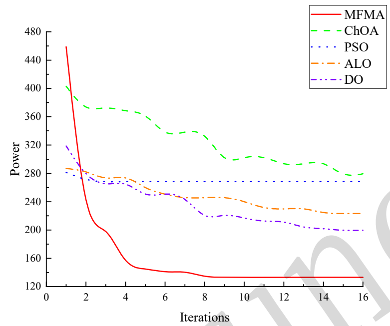

Fig. 9 Newapla

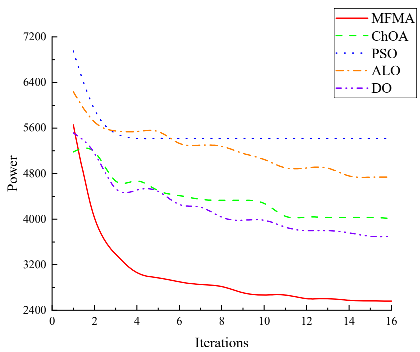

Fig. 10 Alu4

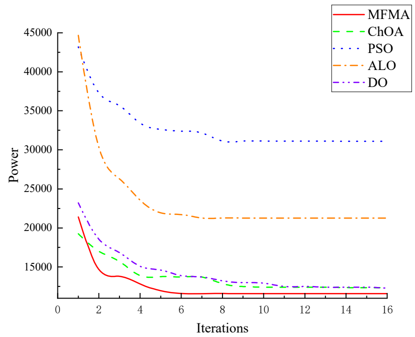

Fig. 11 Table3

6 Conclusions

The XNOR/OR-based power optimization for MPRM logic circuits belongs to a typical three-valued optimization problem. To tackle challenges such as inaccurate searches and susceptibility to local optimization in existing MPRM logic circuits, this paper proposes a power approach based on the MFMA, which not only accelerates convergence speed but also enhances search accuracy, effectively addressing the three-valued combinatorial optimization problem encountered in the power optimization of RM logic circuits. Experimental results conducted on MCNC benchmark circuits, and the IEEE CEC function test set demonstrate that MFMA outperforms existing optimization algorithm by converging faster and identifying optimal solutions more accurately.

In the future, we plan to delve deeper into XNOR/OR-based MPRM logic circuits to develop an integrated approach for optimizing both area and power. This will involve leveraging swarm intelligent optimization algorithms to devise innovation strategies for achieving co-optimization in MPRM logic circuits. Through this research, we aim to enhance the performances of MPRM logic circuits, contributing to advancements in the field of circuit design and optimization.

Contributors

Mengyu ZHANG designed the research. Mengyu ZHANG drafted the manuscript. Zhenxue HE designed the experiment and processed the data. Yijin WANG, Xiaojun ZHAO and Xiaodan ZHANG helped organize the manuscript. Limin XIAO and Xiang WANG revised and finalized the paper.

Conflict of interest

All the authors declare that they have no conflict of interest.

Data availability

Data not available due to [ethical/legal/commercial] restrictions.

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