Enhancing Many-Objective Particle Swarm Optimization with Island Model for Agricultural Optimization

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Keywords: Many-Objective Optimization, Distributed Optimization, Island Model.

Abstract: With the growing complexity of agricultural systems and the need to optimize multiple conflicting objectives simultaneously, traditional optimization methods often struggle to find satisfactory solutions. In this work, we introduce a novel enhancement to the standard Multi Objectives Particle Swarm Optimization (MOPSO) algorithm that significantly improves its effectiveness in handling the diverse and dynamic objectives inherent in agricultural optimization problems. we propose an improvement to the MOPSO algorithm by introducing an islanding technique to promote exploration and exploitation of the many-objective search space. The improved MOPSO algorithm, called I-MOPSO guide the search towards optimal and diverse solutions by dividing the search space into islands and facilitating information exchange between them. We put I-MOPSO into practice and tested it using a series of common many objective optimization algorithms. According to Experimental results show that I-MOPSO is capable of finding high-quality solutions on a variety of test problems, often outperforming the standard MOPSO algorithm and NSGAIII.

1 INTRODUCTION

Numerous many-objective optimization problems (MaOOPs) are encountered in many scientific and engineering study domains. In contemporary agriculture, the optimization of multiple conflicting objectives has become increasingly vital for sustainable and efficient agricultural practices. Farmers and agricultural planners are confronted with complex decision-making scenarios involving trade-offs between maximizing crop yield, enhancing resource utilization efficiency, and ensuring environmental sustainability (Anosri et al., 2023; Liu, Shen, Yang, & Yang, 2013)

When dealing with many-objective optimization problems (MaOPs), optimization issues with four or more competing objectives, certain traditional MOEAs struggle with diversity and convergence, despite their effectiveness for two or three-objective problems.

Nonetheless, a wide variety of research indicates that evolutionary multi-objective optimization (EMOO) algorithms are unable to address MaOO issue. (Rakshit, Chowdhury, Konar, & Nagar, 2020)

The study presented is part of larger context of precision agriculture, an approach that integrates technological advances to optimize farming practices.

The current metaheuristic algorithms still have a number of shortcomings despite the specific advances, including a slow convergence rate, a tendency to trap in local optima, the use of complicated operators, lengthy computation times. In particular, they encounter problems of premature convergence in the case of multimodal and high-dimensional problems. Furthermore, current knowledge indicates that bio-inspired and meta-heuristic algorithms do not always achieve the required performance levels. Their computation time can vary according to the complexity of the problem and the nature of the solution sought. So, some

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Samia, C., Houda, A., Nadia, S. and Nejah, N.
Enhancing Many-Objective Particle Swarm Optimization with Island Model for Agricultural Optimization.
DOI: 10.5220/0013315200003890

In *Proceedings of the 17th International Conference on Agents and Artificial Intelligence (ICAART 2025) - Volume 1*, pages 608-615
ISBN: 978-989-758-737-5; ISSN: 2184-433X

researchers have explored architecture modifications, parameter adjustments and partial operator improvements to overcome these weaknesses. In conclusion, our study seeks to harness the potential of advanced technologies, in particular bio-inspired algorithms, to solve the complex challenges of modern agriculture (Maraveas et al., 2023).

2 METHODOLOGY

2.1 MOPSO

Numerous research has shown the effectiveness of MOPSO in finding optimal solutions for a wide range of real-world problems. (Al-Hassan, Fayek, & Shaheen, 2006)

In (Yang, Tang, Cai, Chen, & Hu, 2022) the authors propose a new cooperative framework with double elite selection and one-dimensional chaotic logistic perturbation (LCSDP), which leads to a considerable increase in convergence and diversity of solutions. Each class performs internal migrations to explore the search space and optimize the solutions in that class. thus, subpopulations exchange information and promote solution diversity. In this way, by using a diversity-based selection technique, the authors are able to prevent an early convergence to a single local optimum. By combining an island model with a local search method (Variable Neighborhood Search). In (Abadlia, Smairi, & Ghedira, 2017, 2018) the authors suggests an enhancement of the MOPSO algorithm that strikes a balance between search space exploration and exploitation. The approach uses local search to maximize local solutions on each island while combining dynamic exchanges and subpopulation movement (islands) to preserve variety.

2.2 Island Model

Island models divide the population into numerous subpopulations known as islands in order to parallelize the evolution process (Wu, Mallipeddi, & Suganthan, 2019). The subpopulations periodically exchange solutions between islands through a process called migration. This migration process plays a crucial role in maintaining the diversity of the islands (Wu et al., 2019; Delaram Yazdani et al., 2023).

The result is a dynamic and hardy population that can react to fresh chances and challenges as a group, guaranteeing the long-term survival of the sub population (Khediri, Nasri, Khan, & Kachouri, 2021).

The idea of changing population size has been applied in a number of evolutionary computation subfields, however its function varies depending on the context (Al-Hassan et al., 2006; Danial Yazdani, Omidvar, Branke, Nguyen, & Yao, 2019).

Every particle is contained within a subswarm of an island, and the topology of the island determines its neighborhoods. Every subpopulation comprises an equal number of individuals and only optimizes a single objective (Yang et al., 2022)(Chnini, Smairi, & Nasri, 2024).

2.3 The Structure and Planning of Islands Topology

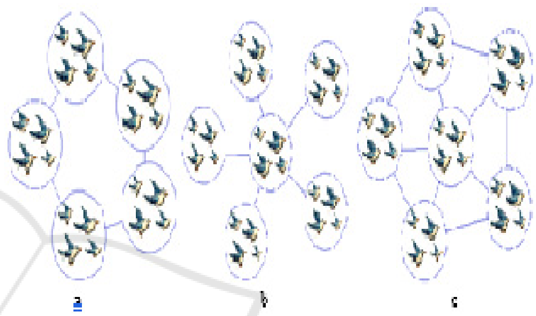

Figure 1: Island topology, a.ring topology, b.star topology, c. grid topology.

The distribution of islands can be designed in many ways according to the topology chosen, such as ring, star or grid patterns. (J. Li & Gonsalves, 2022)

Particles moving between islands usually takes place in a periodic manner and follows a set of rules of migration. This is done to promote diversity and reduce the chances of premature convergence. (Baltazar, 2015; Rakshit et al., 2020) (J. Li & Gonsalves, 2022; Delaram Yazdani et al., 2023).

3 RELATED WORK

The ability of MOPSO algorithm to explore Pareto fronts efficiently and enhance solution convergence has led to various adaptations and improvements tailored to the specific requirements of each application (Anosri et al., 2023).

In (Jithendranath & Das, 2023), authors proposed a new variant of the MOPSO algorithm called NLTV-MOPSO to optimize power flow in island-mode microgrids with photovoltaic generation.

In (H. Li, Wang, Lan, Wu, & Zeng, 2023), the authors proposed a new dynamic multi-objective optimization algorithm based on non-inductive transfer learning, called MSAS-DMOA (Multi-Strategy Adaptive Selection-DMOA). This algorithm uses a combination of adaptive strategies to solve dynamic multi-objective optimization problems (DMOPs). By integrating transfer learning and the MOPSO algorithm, it improves convergence and solution diversity.

A better MOPSO algorithm, known as f-MOPSO-II, has been proposed in (Mansouri, Safavi, & Rezaei, 2022) to optimize reservoir management in the context of climate change.

In (Zarei, Azari, & Heidari, 2022) improved the performance of the NSGA-II and MOPSO algorithms for multi-objective optimization of urban water distribution networks by modifying the decision space. The results showed that modifying the decision space, with the integration of the penalty for exceeding authorized pressure limits.

The authors in (Reddy & Kumar, 2009) have developed an algorithm called EM-MOPSO (Elitist Mutated Multi-Objective Particle Swarm Optimization) for integrated water resource management. Their approach combines elitist and mutation mechanisms to improve solution diversity and accelerate convergence.

4 PROBLEM DEFINITION

A detailed description of the objective functions used in our agricultural optimization study is presented.

4.1 The Optimization Function for Allocating Water

This objective function seeks to minimize the absolute difference between water supply (supplied by sources) and water demand for each site and at each time step. (Nouiri, Yitayew, Maßmann, & Tarhouni, 2015).

$$f_{DS} = Max\left[\left|\sum_{se=1}^{NSE_{max}} FD(se,d,t) - \frac{D(d,t)}{D(d,t)}\right|\right] \quad (1)$$

$$d = 1, \dots, ND_{max} \text{ and } T_{start}, \dots T_{end}$$

4.2 Target Function for Drawdown Reduction

This function assesses how much the exploitation of an aquifer reduces relative drawdowns. (Nouiri, Yitayew, Maßmann, & Tarhouni, 2015).

$$F_D(se,d,t) < F_{max} D(se,d) \ \forall se, \forall d \text{ and } \forall t \quad (2)$$

4.3 Objective Function with Penalty for Maximum Permitted Infraction for Pumping

This function calculates the discrepancy between the maximum pumping rates that have been set and the water flows that the wells have extracted.

$$f_{DD}(s) = Max(\frac{DWDW(w,t) \times VMaxDD(w)}{(Hi(w) - BOTM(w)) \times 1(w)} \quad (3)$$

$$w = 1, \dots, N_{aw} \text{ and } t = T_{start}, \dots T_{end}$$

4.4 Objective Function with Penalty for Exceeding Maximum Acceptable Drawdown

The percentage of the maximum allowable drawdown that is exceeded determines the penalty term. These solutions become less appealing if the drawdown over the threshold because the penalty term raises the value of the objective function.

The problem of water distribution is a complex and many objective problem requires efficient solutions to satisfy often contradictory requirements (Nouiri, Yitayew, Maßmann, & Tarhouni, 2015).

$$VMaxDD(w) = Max(\frac{DWDW(w,t)}{DD_{max}(w)}, 1 \quad (4)$$

$$w = 1, \dots N_{aw} \text{ and } t = T_{start}, T_{end}$$

5 APPROACH

The MOPSO algorithm has proven its effectiveness in reesolving multi-objective problems. However, like many optimization algorithms, it has certain limitations, most notably premature convergence and low diversity in the solutions proposed. In order to improve the quality of solutions and avoid local minima, several adjustments and improvements have been proposed in this work. These seek to improve diversity, optimize exploration, and dynamically modify the algorithm's settings.

Our optimization strategy incorporates the previously mentioned objective functions through the utilization of the MOPSO algorithm, which has been augmented by the island model. In this study, we have selected the ring and star topologies to examine how their interaction dynamics influence solution convergence and diversity.

The I-MOPSO algorithm begins by dividing the global population into several sub-populations, called islands. Each island contains a number of particles, representing potential solutions to the optimization problem. Each algorithm had a population size of 100 particles or solutions, and the maximum number of iterations was set at 600.The particles on each island are randomly initialized in the space of decision variables, and their velocity is set randomly. Each particle has a memory of the best solution it has encountered so far, called bestPosition, as well as an archive of non-dominated solutions.Over the course of iterations, particles update their position in the search space. This update is influenced by three components : inertia (which retains part of the previous velocity), a cognitive term (influenced by the best individual position reached by the particle), and a social term (influenced by a leader selected from the island's archive of non-dominated solutions). Periodically, information is exchanged between islands (each 20 iterations). For I-MOPSO, the star topology is used to connect the islands. Islands share their best solutions to date. A percentage of the best particles on each island migrate to the other islands. This process promotes solution diversity by allowing different sub-populations to exchange information. After each exchange phase, the overall best solution is updated, taking into account the best solutions from all the islands.This island approach enables a more complete exploration of the search space. Each island explores a part of this space independently, thus increasing the diversity of solutions explored.

5.1 Experiments and Metrics

In order to assess the effectiveness of the proposed I-MOPSO method in a star topology, we created a series of tests to investigate how important parameters affect the caliber of the results. The number of islands, the number of particles per island and the migration rate are the relevant parameters. We compare the performance of our I-MOPSO model, NSGA-III and MOPSO in a many-objective optimization problem, specifically applied to water distribution management. Finding out how well these algorithms perform in terms of diversity of generated solutions and convergence to the Pareto front is the aim. We changed the number of islands (3, 5, 10), the number of particles per island (100, 200, 300) and the migrate rates (0.1,0.5,0.8) in order to do this. These factors have a significant impact on the quality of the solutions and the rate of convergence of population-based algorithms.

- **Performance Metrics**

Two indicators are used in this paper to assess the algorithm.On the one hand, the method is evaluated using the coverage metric known as the C metric is a performance indicator used to assess the degree of coverage between two solution sets produced during optimization. (Selvam, Vinod Kumar, & Siripuram, 2017). This quality indicator can be assessed in the manner described below.

$$C = \frac{|\{y \in P_B \exists X \in P_A; x > y\}|}{|P_B|} \tag{5}$$

If $C(P_A, P_B) < C(P_B, P_A)$, the pareto front P_B have the better solutions than P_A (Selvam, Vinod Kumar, & Siripuram, 2017)

In the other hand, hypervolume (J. Li & Gonsalves, 2022; Delaram Yazdani et al., 2023) is also algorithm's evaluation indication. Additionally, it provides a through indication for assessing distribution and convergence. A higher hypervolume reflects better diversity of solutions.

5.2 Results and Discussion

The tables 1, 2 and 3 displays the C metric findings for comparisons between I-MOPSO, NSGA-III and MOPSO as a function of the following algorithm parameters: population size, migration rate, and number of islands. The C measure shows the proportion of solutions on one front that are dominated or covered by those on another front.

Regarding the comparison of MOPSO and I-MOPSO, the latter appears to encompass a significant portion of the MOPSO front. As soon as the population size reaches 200 or more, I-MOPSO gains complete dominance over NSGA-III when the number of islands is set to 3.

Furthermore, NSGA-III is totally overpowered by MOPSO in these configurations, suggesting that NSGA-III performs worse in these circumstances.According to the C metric values, I-MOPSO continuously outperforms NSGA-III across all configurations, attaining 100% coverage for a number of parameter combinations. This indicates that I-MOPSO frequently outperforms MOPSO, especially when the number of islands and population values are high.

Table 1: Performance of the algorithms using C metric (MigRate=0.1).

NumI	Mig Rate	Pop	C(IMOPSO, NSGAIII)	C(NSGAIII, IMOPSO)	C(MOPSO, NSGAIII)	C(NSGAIII, MOPSO)	C(MOPSO, IMOPSO	C(IMOPSO ,MOPSO
3	0.1	100	100	0	100	0	86,96	99,58
		200	100	0	100	0	99,17	97,19
		300	100	0,30	100	0	84,05	98,79
5	0.1	100	100	0,36	100	0	88,85	99,61
		200	100	0	100	0	86,98	97,17
		300	100	0	100	0	95,3	95,85
10	0.1	100	100	0	100	0	80,65	99,59
		200	100	0	100	0	97,07	98,72
		300	100	0	100	0	97,59	99,29

Table 2: Performance of the algorithms using C metric (MigRate=0.5).

Num I	MigRate	Pop	C(IMOP,NSGAIII)	C(NSGAIII,I-MOPS)	C(MOPSO, NSGAIII)	C(NSGAIII,MOPSO)	C(MOPSO,I-MOPSO	C(IMOPSO, MOPSO)
3	0.5	100	100	0	100	1,73	96,54	91,47
		200	100	0	100	0	93,74	96,45
		300	100	0	100	0	67,22	99,97
5	0.5	100	100	0	100	0	99,94	65,65
		200	100	0	100	0,36	84,75	99,27
		300	100	0	100	1,02	86,77	99,33
10	0.5	100	100	0	100	0	94,81	99,47
		200	100	0	100	0	96,89	98,63
		300	100	0	100	0	74,13	99,91

Table 3: Performance of the algorithms using C metric (MigRate=0.8).

Num I	MigRate	Pop	C(IMOP,NSGAIII)	C(NSGAIII,I-MOPS)	C(MOPSO,NSGAIII)	C(NSGAIII, MOPSO)	C(MOPSO,I-MOPSO	C(IMOPSO, MOPSO)
3	0.8	100	100	0	100	0	90,05	97,44
		200	100	0	100	0	90,46	98,99
		300	100	0	100	0	99,84	64,25
5	0.8	100	100	0	100	0	99,31	80,33
		200	100	0	100	0,56	99,66	93,68
		300	100	0	100	1,21	87,76	99,66
10	0.8	100	100	0	100	0	98,86	91,32
		200	100	0	100	0	96,25	99,41
		300	100	0	100	0	98,51	96,06

5.2.1 Impact of the Number of Islands: Number of Islands (Numislands = 3, 5, 10)

The number of islands is a determining factor in the effectiveness of I-MOPSO. With only three islands, I-MOPSO dominates NSGA-III but shows partial coverage over MOPSO. However, I-MOPSO's dominance over MOPSO increases with the number of particles, indicating that even with a small number of islands, I-MOPSO can be competitive if the population size is sufficient. With 10 islands, I-MOPSO reaches its maximum performance, completely dominating NSGA-III and MOPSO in several configurations. Then, a large number of islands gave I-MOPSO increased capacity to effectively explore the Pareto front.

5.2.2 Impact of Number of Particles: (Particles = 100, 200, 300)

With a population of 100, I-MOPSO manages to dominate NSGA-III but shows partial coverage of MOPSO's Pareto front, particularly when the number of islands is minimal. By increasing the population to 200, I-MOPSO improves its coverage, achieving complete domination of NSGA-III and superior coverage than MOPSO. This suggests that a population of 200 is sufficient to enable I-MOPSO to generate a high-quality Pareto front in moderate migration and island number configurations.

5.2.3 Impact of Migration Rate (MigrationRate=0.1, 0.5,0.8)

With a migration rate of 0.8, I-MOPSO achieves high dominance results, indicating that the frequent exchange of individuals between islands improves the diffusion of optimal solutions. This high migration rate promotes rapid convergence towards the Pareto front while maintaining a diversity of solutions, which is essential for the quality of the front generated. A lower migration rate might retain more local diversity, but could slow convergence.

A migration rate of 0.8 appears to be the best setting for I-MOPSO overall, providing for a balance between Pareto front exploration and exploitation.

Analyzing the findings reveals that I-MOPSO performs the best in most configurations, particularly when paired with a big population (200–300), a migration rate of 0.8, and a high number of islands.

In order to evaluate the I-MOPSO algorithm's performance, we measured the mean hypervolume (Mean Hypervolume) and the standard deviation of hypervolume (Std Hypervolume) throughout the last 50 iterations of each execution. Comparative analysis of the obtained hypervolumes provides essential information on how parameters affect the algorithm's ability to efficiently search the space of solutions while maintaining a steady convergence towards the Pareto front. These findings make it possible to determine the best configurations for many objective problems in order to maximize solution diversity and convergence.

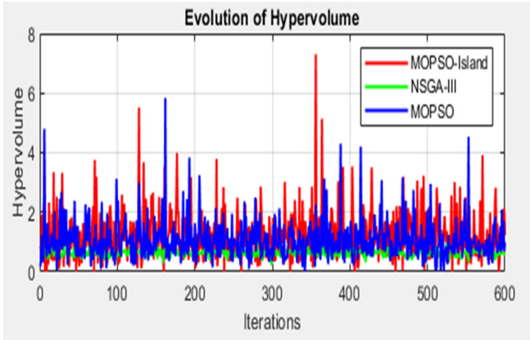

Figure 2: Comparison of hypervolume evolution for over iterations.

The figure 2 illustrates differences in the stability and efficiency of algorithms for maximizing hypervolume over the course of iterations. I-MOPSO seems to indicate higher variability, with multiple notable peaks, which would suggest a more intensive search for solutions. Reflecting a more gradual convergence, NSGA-III exhibits fewer fluctuation and is comparatively stable. In terms of hypervolume values, MOPSO exhibits regular fluctuations but is still generally less effective than I-MOPSO.

By obtaining a greater mean hypervolume, I-MOPSO continuously surpasses NSGA-III and MOPSO, demonstrating its superior exploration and exploitation capabilities. whereas NSGA-III consistently achieves the lowest mean hypervolume. I-MOPSO maintains its edge in the majority of cases (table 4,5 and 6), whereas NSGA-III becomes more competitive as migration rates rise.

Both I-MOPSO and MOPSO's mean hypervolume improves with population size, with I-MOPSO maintaining a slight advantage. NSGAIII continues to be the least competitive in mean hypervolume and stability, despite a minor improvement with bigger populations.

Table 4: Means ans stds Hypervolume values throughout the last 50 iterations (MigRate=0.1).

NumI	MigRate	Pop	I-MOPSO		NSGAIII		MOPSO	
			Mean Hypervolume	Std Hypervolume	Mean Hypervolume	Std Hypervolume	Mean Hypervolume	Std Hypervolume
3	0.1	100	1.223e+00	8.147e-01	6.029e-01	1.124e-01	1.109e+00	6.185e-01
		200	1.256e+00	9.117e-01	6.321e-01	1.324e-01	1.171e+00	7.330e-01
		300	2.106e+00	1.768e+00	6.290e-01	1.263e-01	1.554e+0	1.020e+00
5	0.1	100	1.117e+00	7.743e-01	6.270e-01	1.081e-01	9.974e-01	6.410e-01
		200	1.501e+00	9.620e-01	6.473e-01	1.251e-01	1.472e+00	1.016e+00
		300	1.725e+00	1.419e+00	6.188e-01	1.208e-01	1.494e+00	1.087e+00
10	0.1	100	1.313e+00	6.939e-01	6.403e-01	1.447e-01	1.062e+00	8.615e-01
		200	1.867e+00	1.356e+00	6.125e-01	1.274e-01	1.400e+00	7.621e-01
		300	2.393e+00	1.770e+00	5.913e-01	1.070e-01	1.459e+00	9.708e-01

Table 5: Means ans stds Hypervolume values throughout the last 50 iterations(MigRate=0.5).

NumI	MigRate	Pop	I-MOPSO		NSGAIII		MOPSO	
			Mean Hypervolume	Std Hypervolume	Mean Hypervolume	Std Hypervolume	Mean Hypervolume	Std Hypervolume
3	0.5	100	1.163e+00	5.071e-01	6.250e-01	1.186e-01	1.210e+00	6.833e-01
		200	1.781e+00	1.349e+00	6.120e-01	1.000e-01	1.411e+00	8.732e-01
		300	1.772e+00	1.299e+00	5.953e-01	1.246e-01	1.578e+00	1.023e+00
5	0.5	100	9.974e-01	6.986e-01	6.438e-01	1.461e-01	9.559e-01	4.154e-01
		200	1.745e+00	1.281e+00	6.104e-01	1.206e-01	1.476e+00	9.575e-01
		300	1.781e+00	1.191e+00	6.105e-01	1.117e-01	1.511e+00	1.002e+00
10	0.5	100	1.290e+00	8.168e-01	6.376e-01	1.225e-01	1.149e+00	5.246e-01
		200	2.269e+00	1.862e+00	6.040e-01	1.153e-01	1.140e+00	5.567e-01
		300	2.353e+00	1.957e+00	6.174e-01	1.264e-01	1.315e+00	8.303e-01

Table 6: Means ans stds Hypervolume values throughout the last 50 iterations (MigRate=0.8).

NumI	MigRate	Pop	I-MOPSO		NSGAIII		MOPSO	
			Mean Hypervolume	Std Hypervolume	Mean Hypervolume	Std Hypervolume	Mean Hypervolume	Std Hypervolume
3	0.8	100	1.092e+00	5.180e-01	6.267e-01	1.150e-01	1.254e+00	7.429e-01
		200	1.314e+00	8.915e-01	6.463e-01	1.200e-01	1.255e+00	9.626e-01
		300	1.975e+00	1.700e+00	6.481e-01	1.320e-01	1.889e+00	1.404e+00
5	0.8	100	1.175e+00	7.390e-01	6.455e-01	1.243e-01	1.133e+00	6.587e-01
		200	1.789e+00	1.741e+00	6.707e-01	1.688e-01	1.420e+00	8.965e-01
		300	1.635e+00	1.001e+00	6.097e-01	1.261e-01	1.428e+00	9.532e-01
10	0.8	100	1.393e+00	9.896e-01	6.240e-01	1.340e-01	9.884e-01	4.672e-01
		200	1.501e+00	1.061e+00	6.146e-01	1.033e-01	1.601e+00	1.135e+00
		300	2.760e+00	1.763e+00	6.066e-01	1.202e-01	1.345e+00	1.097e+00

6 CONCLUSIONS

In this study, we have proposed an innovative many-objective approach based on the Island model to solve the water distribution optimization problem, taking into account several conflicting objectives. The distinguishing feature of this method is its decomposition of the problem into several subpopulations spread over islands, enabling more efficient exploration of the solution space by combining local search and migration strategies between islands.

Our experiments on agricultural optimization problems show that this method can effectively find many high-quality solutions. When compared to other evolutionary algorithms, it does better at solving agricultural problems with many objectives. This study improves optimization techniques for agriculture and opens up new avenues for future research in this area. Finally, our analysis shows that the adjustment of parameters such as the number of islands and particles plays an essential role in improving the performance of our model. The proposed approach thus offers a robust and flexible method, which can be adapted to a wide variety of many-objective problems in the field of resource optimization.

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