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Hybrid Approach of Water Cycle Algorithm with Artificial Bee Colony

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Abstract
This paper represents a combined optimization of both Water Cycle (WCA) Algorithm and Artificial Bee Colony (ABC) Algorithm to improve optimization for solving complex problem. The fundamental concepts and ideas which proposed the combination of both algorithm is inspired from nature and based on the observation of water cycle process and how rivers and streams flow to the sea in the real world. This algorithm testing in the Matlab 2024b apply functions (F1 to F23) and the obtained results are also compared with WCA algorithms. According to the results, the algorithm that found the best solution in 15293.65238 (F3) of the test functions is WCA. The performance of the proposed hybrid algorithm is evaluated on a set of benchmark functions and compared with the standard WCA and ABC algorithms.

Keyword-
Hybridization, Water Cycle Algorithm, Artificial Bee Colony, Optimization, Benchmark.

1. Introduction

In a variety of fields, such as engineering, operational research and machine learning, optimisation is very essential for the solution of complex real-world problems. Because they can easily & effectively explore large search spaces [1]. Many real-world engineering optimisation problems are very complicated in nature and quite difficult to solve. When there is more than one local optimum, the results may depend on the selection of the starting point for which the obtained optimal solution may not necessarily be the global optimum.

These techniques which are inspired by natural phenomena have gained significant attention in recent times. The Water Cycle Algorithm (WCA) and Artificial Bee Colony (ABC) are widely used for optimisation problems.

The Water Cycle Algorithm (WCA) is derived from the natural water cycle process, where rivers and streams flow towards the sea in the real world. Despite having great global search capabilities, WCA ends too soon, which limits its ability to thoroughly explore all areas. However, the Artificial Bee Colony (ABC) algorithm is a swarm-based optimisation technique that follows honeybee foraging. To balance both extraction and exploration, it breaks down the population into different roles. Still, particularly in high-dimensional search spaces, ABC could be experiencing difficulties in calculating the solution.

This study suggests a hybrid strategy consisting of WCA and ABC, applying local refinement features of ABC and the global search power of WCA to overcome the limitation of these separate algorithms. Increasing convergence speed, preventing premature stagnation, and improving solution accuracy tend to be the primary goals of this hybridisation.

2. Literature Review

In order to improve the effectiveness and precision of resolving challenging problems across different fields, optimisation methods have been thoroughly researched. Because of their adaptability and resilience, optimisation algorithms – which draw motivation from biological and natural processes – have become more popular. The strengths, limitations, and potential for combination of the water cycle algorithm (WCA), artificial

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bee colony (ABC) algorithms, and hybrid optimisation technique are presented in this section.

2.1 Water Cycle Algorithm (WCA)

Eskander et al. (2012) presented the Water Cycle Algorithm (WCA), an optimisation method inspired by nature and based on the real water cycle process. It approximates the movement of solutions towards an ideal point by modelling the flow of rivers and streams into the sea. WCA has been effectively used for solving problems.

WCA has a major drawback because it commonly converges too soon, resulting in stagnation in local optima, despite the improvement in global search and convergence speed. Researchers are trying to improve selection strategies [2] and adaptive stream flow rates [3] to work near this. But these improvements persist in difficulty keeping problems in balance.

2.2 Artificial Bee Colony

In 2005, Karaboga presented the Artificial Bee Colony (ABC) Algorithm, an optimisation approach based on swarm intelligence that mimics honeybee foraging behaviour. ABC separates the population of honeybees into three groups: scout bees (explorers), onlooker bees (solution selectors), and employed bees (solution generators). ABC has proven successful in machine learning [4], image processing [5], and wireless sensor networks [6] due to this separation, which enables it to successfully combine exploitation and exploration.

However, ABC may show slow convergence and inefficient local search in high-dimensional search spaces. Combining hybrid approaches with other algorithms, like particle swarm optimisation [7] and modified search equation . Researchers have attempted to improve ABC. [8] In response to these studies, ABC's performance can be increased by combining it with an accurate global search algorithm.

2.3 Hybrid Optimisation Strategy

Since hybrid optimisation strategy aims to reduce the weakness of individual algorithms while utilising their strength, they have drawn a lot of interest. Hybridising WCA and other algorithms has become the subject of several studies.

Though WCA and ABC have been separately improved, their individual shortcomings – WCA's initial convergence and ABC's weak exploitation – suggest that a hybrid WCA-ABC approach might be valuable. This work presents a hybrid WCA-ABC approach that combines WCA's stream-based movement with ABC's swarm-based adaptation. The hybrid algorithm requires improving convergence speed, solution accuracy, and robustness in solving difficult optimisation problems by way of this operation.

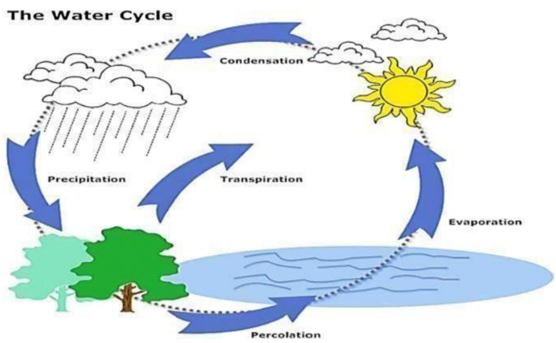

Fig-1: Simplified diagram of the hydrologic cycle (water cycle).

3. Pseudocode

Here first algorithm is the hybrid WCA-ABC algorithm.

1) Set the ABC parameters (EB, OB, SB), WCA parameters (Nr, Ns, EC), population size (N), and maximum iterations (MaxIter) to their initial values.
2) Randomly create the first population of N ideas for solutions.
3) Determine each solution's fitness f(X).
4) Assign the best option to "Sea" and the others to "Rivers" and "Streams".

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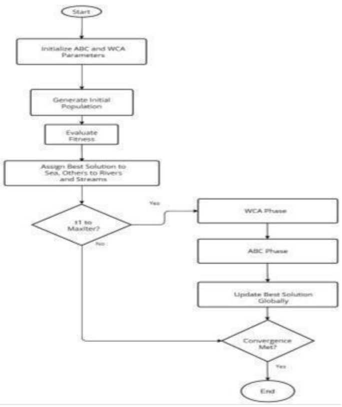
5) FOR t = 1 to MaxIter DO:
a) WCA Phase (Global Search):
i) Direct streams to the appropriate rivers.
ii) Point rivers in the direction of the sea.
iii) If nothing changes, use the evaporation conditions (EC check).
iv) Analyze the best solution found thus far.
b) ABC Phase, or Local Search.
i) Based on the present solution, create a new candidate solution for every bee that is involved. Use fitness and greedy selection.
ii) Measure the probability of each response.
iii) For every onlooker bee, choose to modify a probability-based solution. Make use of the greedy selection theory.
iv) For every scout bee, replace out stale solutions with fresh, arbitrary ones.
c) Update the best solution around the world.
d) EXIT if the convergence requirements are satisfied
6) Provide the best answer you could discover.

3.1 Flowchart



3.2 Table

Benchmark Functions

Table 2: Standard UM benchmark functions

Functions	Dimensions	Range	f_{min}
$F_1(S) = \sum_{m=1}^{z} S_m^2$	(10,30,50,100)	[-100 , 100]	0
$F_2(S) = \sum_{m=1}^{z} \lvert S_m \rvert + \prod_{m=1}^{z} \lvert S_m \rvert$	(10,30,50,100)	[-10 ,10]	0
$F_3(S) = \sum_{m=1}^{z} (\sum_{n-1}^{m} S_n)^2$	(10,30,50,100)	[-100 , 100]	0
$F_4(S) = max_m\{\lvert S_m \rvert, 1 \le m \le z\}$	(10,30,50,100)	[-100 , 100]	0
$F_5(S) = \sum_{m=1}^{z-1} [100(S_{m+1}-S_m^2)^2 + (S_m - 1)^2]$	(10,30,50,100)	[-38 , 38]	0
$F_6(S) = \sum_{m=1}^{z} ([S_m + 0.5])^2$	(10,30,50,100)	[-100 , 100]	0
$F_7(S) = \sum_{m=1}^{z} mS_m^4 + random\,[0,1]$	(10,30,50,100)	[-1.28, 1.28]	0
Functions	**Dimension**	**Range**	f_{min}
$F_8(S) = \sum_{m=1}^{z} -S_m sin(\sqrt{\lvert S_m \rvert})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z} [S_m^2 - 10cos\,(2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp\,(-0.2\sqrt{\left(\frac{1}{z}\sum_{m=1}^{z} S_m^2\right)}) - exp\,(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(10,30,50,100)	[-32,32]	0
$F_{11}(S) = 1 + \sum_{m=1}^{z} \frac{S_m^2}{4000} - \Pi_{m=1}^{z} cos\frac{S_m}{\sqrt{m}}$	(10,30,50,100)	[-600, 600]	0
$F_{12}(S) = \frac{\pi}{z}\left\{10\,sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\right\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_m+1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(10,30,50,100)	[-50,50]	0
$F_{13}(S) = 0.1\{sin^2(3\pi S_m) + \sum_{m=1}^{z}(S_m - 1)^2[1 + sin^2(3\pi S_m + 1)] + (x_z - 1)^2[1 + sin^2 2\pi S_z)]$	(10,30,50,100)	[-50,50]	0
Functions	**Dimensions**	**Range**	f_{min}
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5\frac{1}{n+\sum_{m=1}^{z}(S_m - b_{mn})6}]^{-1}$	2	[-65.536, 65.536]	1
$F_{15}(S) = \sum_{m=1}^{11} [b_m - \frac{S_1(a_m^2 + a_m S_2)}{a_m^2 + a_m S_3 + S_4}]^2$	4	[-5, 5]	0.00030
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1S_2 - 4S_2^2 + 4S_2^4$	2	[-5, 5]	-1.0316
$F_{17}(S) = (S_2 - \frac{5.1}{4\pi 2}S_1^2 + \frac{5}{\pi}S_1 - 6)^2 + 10(1-\frac{1}{8\pi})cosS_1 + 10$	2	[-5, 5]	0.398
$F_{18}(S) = \left[1 + (S_1 + S_2 + 1)^2 (19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1S_2 + 3S_2^2)\right] \times \left[30 + (2S_1 - 3S_2)^2 (18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1S_2 + 27S_2^2)\right]$	2	[-2,2]	3
$F_{19}(S) = -\sum_{m=1}^{4} d_m\, exp\,(-\sum_{n=1}^{3} S_{mn}(S_m - q_{mn})^2)$	3	[1, 3]	-3.32
$F_{20}(S) = -\sum_{m=1}^{4} d_m\, exp\,(-\sum_{n=1}^{6} S_{mn}(S_m - q_{mn})^2)$	6	[0, 1]	-3.32
$F_{21}(S) = -\sum_{m=1}^{5} [(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0,10]	-10.1532
$F_{22}(S) = -\sum_{m=1}^{7} [(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.4028
$F_{23}(S) = -\sum_{m=1}^{7} [(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.5363

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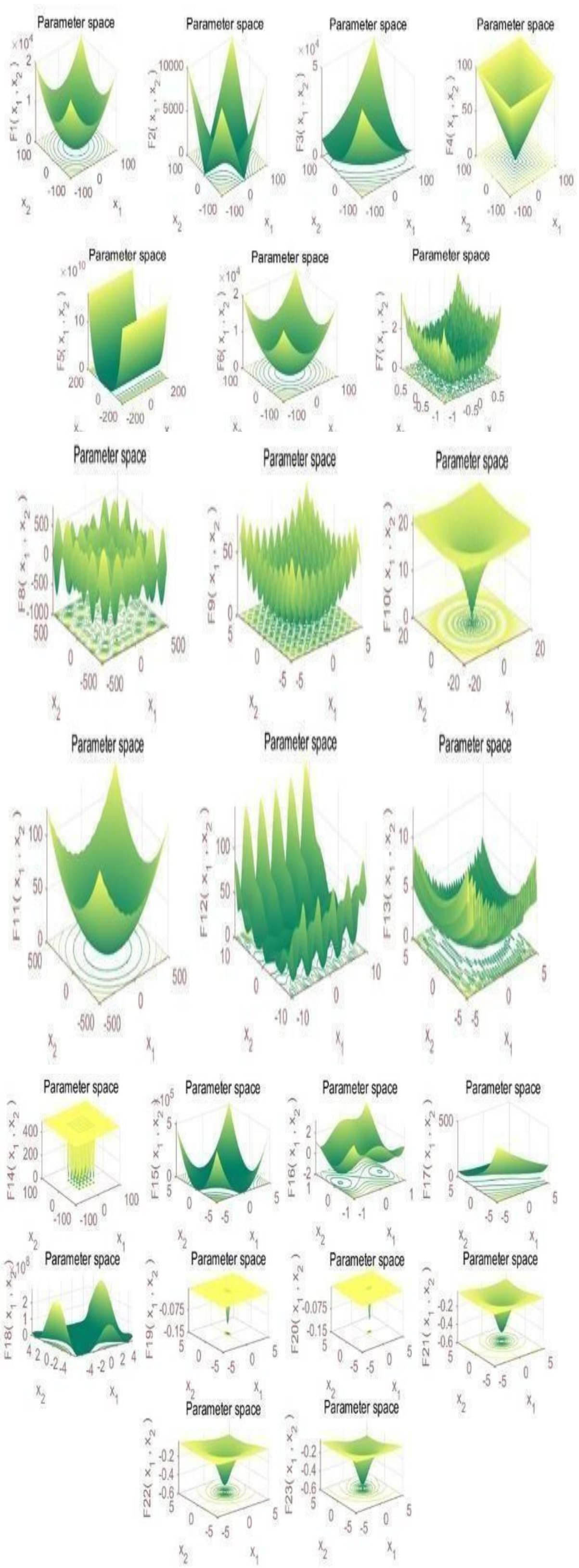

4. Results and Discussion

The WCA algorithm is applied to each problem and the results are compared with other used hybridization algorithms.

Function	Best Score of WCA	Best Score of Hybrid WCA & ABC
F1	1.4029E-07	2.549284661
F2	0.000102154	0.063183005
F3	9.207703317	15293.65238
F4	16.07400225	53.16716545
F5	148.4035472	727.8413446
F6	1.12817E-07	3.736831669
F7	1.015002621	0.237870692
F8	-8618.272565	-8581.742037
F9	60.69241685	173.4389264
F10	2.662885238	1.44843944
F11	2.30183E-07	1.032329648
F12	0.103669626	66.78419464
F13	7.30539E-07	60.57846801
F14	0.998003838	0.998003838
F15	0.000307486	0.000772985
F16	-1.031628453	-1.031628453
F17	0.397887358	0.397887358
F18	3	3
F19	-3.862782148	-3.862782148
F20	-3.20310205	-3.321995172
F21	-10.15319968	-10.15319968
F22	-2.751933564	-3.722509131
F23	-10.53640982	-10.53640928

5. Conclusion

This paper presented a Hybrid Water Cycle Algorithm (WCA) and Artificial Bee Colony (ABC) to improve the optimisation technique for solving constraints in the real world. The hybrid approach demonstrated better stability and improved performance across multiple benchmark functions. The hybrid algorithm is a reliable optimisation approach that performs better than WCA and ABC according to experimental results. The result showed that the hybrid strategy improves speed and balances exploitation and exploration more effectively than WCA or ABC individually. In fact, although the exploratory ability of the hybrid approach depends on the complexity of the problem, the optimisation results showed that it might be a suitable alternative strategy for finding optimised solutions for different aspects. Hybridization of Water Cycle Algorithm (WCA) with Artificial Bee Colony (ABC) Algorithm was tested on 23 Benchmark functions (F1-F23) among these the most optimal result was observed for function F3(15293.65238).

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This shows the effectiveness of this hybrid strategy for solving complex problem.

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